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How Do Households Respond to Job Loss? Lessons from Multiple High-Frequency Datasets†

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How much and through which channels do households self-insure against job loss? Combining data from a large bank and from government sources, we quantify a broad range of responses to job loss in a unified empirical framework. Cumulated over a two-year period, households reduce spending by 30 percent of their income loss. They mainly self-insure through adjustments of liquid balances, which account for 50 percent of the income loss. Other channels—spousal labor supply, private transfers, home equity extraction, mortgage refinancing, and consumer credit—contribute less to self-insurance. Both overall self-insurance and the channels vary with household characteristics in intuitive ways. (*JEL* D12, G21, G51, J64, J65)

For most people, job loss is the main source of idiosyncratic earnings risk (Guvenen et al. 2021). Losing a job typically leads to a large and persistent drop in income, even when accounting for social insurance. Several studies show that household consumption also drops following job loss, but more moderately than income. For example, recent evidence from the United States (Ganong and Noel 2019) and Sweden (Landais and Spinnewijn 2021) shows that the drop in spending amounts to 20–30 percent of the drop in income at the onset of unemployment.[1]

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[1] Other studies documenting persistent income losses include Jacobson, LaLonde, and Sullivan (1993); Davis and Wachter (2011); Kawano and Lalumia (2015); Flaaen, Shapiro, and Sorkin (2019); and Seim (2019). For studies documenting drops in spending, see, e.g., Gruber (1997), Browning and Crossley (2001, 2009), Hendren (2017), Ganong and Noel (2019), and Landais and Spinnewijn (2021).

While these findings imply a significant degree of self-insurance against job loss, they say nothing about how households self-insure: Do they draw on their savings, borrow in financial markets, or raise liquidity from elsewhere? And does the relative importance of these responses—as well as the overall degree of self-insurance—vary systematically with differences in the costs and opportunities they face when deciding how to adapt? These questions are crucial for understanding the determinants of households' ability to smooth consumption when they experience job loss, which, in turn, has important implications for the design of social insurance schemes (Baily 1978; Chetty 2006).

Conceptually, self-insurance against job loss can take three forms. To the extent that spending drops less than income, the difference must be matched by a reduction in saving, an increase in borrowing, or an increase in funds from other sources.[2] Various response margins within each of these categories have been proposed by different strands of literature: Households can raise money inflows from other sources through an increase in spousal labor income (Lundberg 1985; Cullen and Gruber 2000; Stephens 2002; Hardoy and Schøne 2014; Halla, Schmieder, and Weber 2020) or through increases in private transfers from family and friends (Altonji, Hayashi, and Kotlikoff 1997; McGarry 2016). They can reduce debt repayments or increase borrowing by taking up alternative mortgage products or tapping into home equity (Hurst and Stafford 2004; Cocco 2013) or by borrowing more through unsecured lines of credit (Sullivan 2008). They can reduce saving by running down their buffer stock of liquid assets (Carroll 1997; Basten, Fagereng, and Telle 2016). Existing studies within these strands of literature typically focus on a single response margin, with samples, data types, and methods varying across studies. Little is known about the relative importance of the various self-insurance responses and how the strength of the responses relates to household characteristics.

In this paper, we estimate the effects of job loss on income, spending, and self-insurance responses in a unified empirical framework. We analyze all responses at the monthly frequency for the same sample of households, applying the same definition of job loss and using the same research design, which allows us to determine the relative importance of each mode of self-insurance for the average person. We then analyze whether and how households differ in how much they smooth spending in the face of job loss and in the ways they achieve this. We focus on four characteristics that are informative about the costs and opportunities households face when experiencing job loss: liquid asset holdings, the food budget share, marital status, and the age of the person losing a job.[3]

To do this, we turn to Denmark, where a unique research data infrastructure makes it possible to combine data from many different sources. Specifically, we merge transaction-level data from the largest bank in Denmark with administrative

[2] We use the term *self-insurance* to refer to all responses that weaken the contemporaneous impact of shocks to income on household consumption. These include responses that counteract the drop in income, such as higher spousal labor supply, as well as pure consumption-smoothing responses that transfer liquidity across time—i.e., borrowing or saving.

[3] Landais and Spinnewijn (2021) note that a key factor in households' reponses to job loss is the shadow price of raising funds to sustain consumption, which depends on, among other things, the cost of liquidity obtained from financial markets and the utility cost of expanding the spouse's labor supply.

data from multiple government registers. The combined dataset has several attractive properties: First, the monthly frequency enables sharp empirical identification in an event-study design. Second, the detailed transaction data allow us to construct precise and comprehensive measures of monthly saving and spending, including subcategories of total spending, and observe inflows that are typically unrecorded in government registers, such as person-to-person transfers.[4] Third, the data include detailed demographic information, which enables us to identify spousal labor supply responses and to study outcomes at the household level. Fourth, the data from government registers allow us to identify payments from employers and government agencies in the transaction data and thus separate them from private transfers from persons outside the household. Fifth, linking the transaction data to administrative data for the full population enables us to address concerns about completeness and representativeness that typically arise in studies using transaction data from a single provider (Baker 2018). In short, the data allow us to provide a complete account of how households respond to job loss. We document this by showing that the reponses we consider add up to match the size of the income loss.

Our first set of results is concerned with the effects of job loss for the average job loser. Consistent with existing studies from other countries, we document a significant and persistent income loss. Spending also falls, but not nearly as much: Over the two years following job loss, the cumulative spending drop amounts to 30 percent of the cumulative income loss. This leaves a gap of 70 percent that reflects self-insurance. We find that this gap is filled by a drop in net saving in liquid assets (~50 percent), an increase in private transfers and other income (~10 percent), an increase in spousal labor supply (~5 percent), and a drop in net debt repayments (~5 percent). The latter is partly driven by refinancing to mortgage loans with lower monthly payments, whereas we find no effect on home equity extraction.

The second set of results documents that household responses to job loss are heterogeneous and suggests that they are systematically shaped by differences in the costs associated with the various response margins. For example, households with plenty of liquid assets before job loss can adjust more easily by decumulating, and therefore face a lower cost of sustaining spending through this channel, than households with few liquid assets. Indeed, we find that households in the latter group decumulate less and reduce spending much more than those in the former group. Similarly, we find larger spending reductions among the young—who hold small amounts of liquid assets—than among the old, despite a larger income loss in the latter group. Spending reductions are also larger in single-adult households than in two-adult households, reflecting the former's inability to generate alternative income via increased spousal labor supply. Finally, to capture differences in the marginal cost of cutting spending, we split households by how much of their budgets they spend on food in the months before job loss. Those with a relatively high food budget share presumably face a higher marginal utility cost, and they do indeed

[4] Other studies impute spending from annual information about income and changes in assets and liabilities (e.g., Browning and Leth-Petersen 2003; Landais and Spinnewijn 2021) or use self-reported measures of spending (e.g., Parker and Souledes 2019; Kreiner, Lassen, and Leth-Petersen 2019).

reduce spending less. Instead, they raise more liquidity through increases in spousal labor supply and, especially, private transfers and other income.

With these results, our study provides the first complete account of how households self-insure against the income loss associated with job loss, allowing us to assess the relative importance of all empirically relevant response margins. Broadly speaking, the responses fall into two classes of behavior. The first class comprises responses that affect the household's consumption possibilities by providing new inflows from alternative sources to compensate for the loss of labor income (increases in spousal income, private transfers). The second class consists of smoothing responses that change the timing of consumption (adjustments of net saving, borrowing, and debt repayments). Our results show that smoothing responses are, empirically, far more important than new inflow responses for the average person experiencing job loss; however, the results also highlight that the relative importance of the two classes of behavior varies across households in intuitive ways. Pure consumption-smoothing responses are less dominant for households with few liquid assets and among those with better options for raising income from other sources.

The rich combination of data sources allows us to address potentially important concerns that normally arise when using transaction data from a single provider. First, to address concerns about completeness, we use information from the Danish Tax Authority about all accounts held in Danish banks to identify households who are exclusive Danske Bank customers and show that our results also hold in this smaller subsample. Second, to address concerns about representativeness, we use the population-wide registry data and assess how our analysis sample of Danske Bank customers compares to the full population of job losers. We then show that our results are virtually unchanged when we reweight observations to make the sample match the population in demographic characteristics.

Another potential concern is about the relevance of our findings for countries with different unemployment insurance systems. In Denmark, the maximum duration of benefits is two years, which is long by international standards, while the effective replacement at the average wage is in line with other developed countries (OECD 2021). Supporting the case for external validity, we note that our estimates of spending responses to unemployment are comparable to estimates for Canada (Browning and Crossley 2001), the United States (Ganong and Noel 2019), and Sweden (Kolsrud et al. 2018; Landais and Spinnewijn 2021). Other aspects of our analysis also parallel findings from other countries: Landais and Spinnewijn (2021) use annual data on labor market performance, income, and wealth from public administrative registers in Sweden. Like them, we find that access to liquidity matters for the spending response, and that the effect on spousal labor income (the added-worker effect) is limited. Finally, we note that while the quantitative effects of the various responses may depend on the exact institutional setting, the qualitative differences revealed by our heterogeneity analysis reflect differences in fundamental household characteristics and should therefore depend less on the institutional setting.

The paper proceeds as follows: Sections I–III present background information on the institutional setting, data, and empirical methods. Section IV presents our main results for the average person experiencing job loss, while Section V elaborates on these results by presenting additional analysis for selected responses. Section VI presents our results on heterogeneity in responses. Section VII concludes.

I. The Danish Institutional Setting

Labor Market.—The Danish labor market is characterized by flexible hiring and firing rules for employers, combined with high income security for employees (Andersen and Svarer 2007). Dismissing workers is low-cost for employers compared to many other countries (OECD 2013). The notice period is typically three to six months for white-collar workers but shorter for blue-collar workers (Scheuer and Hansen 2011). This means that many laid-off workers have a few months to prepare for the impending drop in wage income.

The unemployment insurance system is partly funded by workers' contributions and partly by the government. Members of the insurance system receive benefits worth 90 percent of the pre-unemployment wage up to a cap of around $3,000 per month. Because of this cap, actual replacement rates are considerably lower for many wage earners and only slightly above the average level in other OECD countries.[5] Benefits are taxed the same way as labor income. The maximum duration of UI benefits is two years. This provides high income security compared to many other countries, including the United States, where the maximum duration is typically six months. Unemployed workers who are ineligible for UI benefits may receive a means-tested basic social transfer of around $1,700 per month, with a supplement for families with children. Other government transfers, such as housing support and child benefits, are also income dependent and may help reduce the income drop after job loss.

Financial Markets.—Households in Denmark buy financial services from two main types of financial institutions: retail banks and specialized mortgage banks. Retail banks offer a wide range of financial services, including deposit accounts and various credit facilities. Mortgage banks only offer mortgage loans financed by covered bonds, and they offer both fixed and adjustable-rate mortgages, with and without interest-only payments, and with a duration of up to 30 years. Contracts with built-in insurance against unemployment do not exist in Denmark. At origination, mortgage borrowers always face the current rate in the covered bond market. The highest permissable loan-to-value ratio at origination is 80 percent.[6] Fixed-rate mortgages can be refinanced at a fairly low cost (Andersen et al. 2020). Mortgage debt is full recourse in Denmark, and defaults are rare (Kreiner, Leth-Petersen, and Willerslew-Olsen 2020).

[5] In the period we study (2009–2016), the replacement rate at a three-month unemployment spell for a single person with no children earning the average wage was 62 percent in Denmark, against an OECD average of 57 percent (OECD 2021). For a couple with two children where both adults earn the average wage, the corresponding numbers were 80 percent and 79 percent, respectively.

[6] Homeowners can go beyond the 80 percent limit by taking out additional collateralized loans from retail banks, but these are more expensive.

Payment System.—The payment landscape in Denmark is highly digitalized. Almost all bill payments are made electronically, with over 95 percent of Danish households paying bills by direct debit (Danish Competition and Consumer Authority 2014). Card usage is higher in Denmark than in any other European country, checks are no longer in use, and only 16 percent of the value of point-of-sale retail transactions is in cash, compared to 39 percent for the United States (Danmarks Nationalbank 2017; Greene and Stavins 2018). These features limit the problem of "invisible" cash transactions when using bank transaction data to measure spending.

II. Data Construction

We link monthly information about individuals from multiple administrative data sources using a unique personal identity number assigned to all Danish residents. The combined data allow us to track individuals and their spouses from January 2009 to December 2016. This section describes the data and the construction of key variables. We deflate all nominal variables by Statistics Denmark's consumer price index (Statistics Denmark 2019j). Online Appendix A contains further details about variable definitions.

Employment.—We identify employment, job separations, periods of unemployment, and the individual's main employer using population-wide monthly payroll records collected by the Danish Tax Agency and made available to researchers by Statistics Denmark (Statistics Denmark 2019b, f). Employers must report wages for each employee to the tax agency, and government agencies must report income transfers. Evasion is minimal (Kleven et al. 2011; Alstadsæter, Johannesen, and Zucman 2019). The records are used for tax collection and for computation of official employment statistics. Each record contains information about the gross amount paid, the month in which the amount was earned, a unique employer ID and sector code (for wage payments), and a transfer program code (for income transfers).

Income, *Spending*, *Saving*, *and Nonmortgage Debt Repayments*.—We use transaction and account records from the largest bank in Denmark ("Danske Bank," henceforth "the bank"; Danske Bank 2018). More than one third of the Danish adult population are in our data. The records contain information on all deposit and loan account balances, as well as detailed information about all transactions in each account.

We adopt a broad definition of household disposable income, equal to the sum of external inflows to the household's bank accounts. To construct this measure, we focus on specific types of account inflows: first, direct deposits, which include all wage, pension, and government transfer income; second, person-to-person transfers that originate from outside the household, which include transfers from family members and friends; and third, cash deposits into accounts. We then break household disposable income down into wage income for each household member, income transfers from the government, and private transfers and other income. To do this, we combine the transaction data with the payroll data from the tax authority, as described above, allowing us to identify which income payments are from employers or government agencies (see online Appendix C for details).

For spending, we focus on three types of payments—debit or credit card, in-store mobile, and bills—as well as cash withdrawals from ATMs (see details in online Appendix B). For card and in-store mobile payments, we can categorize the type of spending using the recipient's four-digit Merchant Category Code (MCC), which is an international standard for classifying merchants by the types of goods and services they provide. For bill payments, we know the identity of the creditor for each transaction. The bank maintains a grouping of creditors into categories that correspond to the MCC grouping, and we use this to categorize bill payments into the same groups as for card and mobile payments. To construct our baseline measure of monthly expenditure, we sum outgoing transactions by each of the payment methods and all cash withdrawals from ATMs. We exclude tax and debt payments as well as fees paid to the bank. Figure A2 in the online Appendix shows that our spending measure tracks measures from more traditional sources closely in the cross-section as well as over time.

We measure net repayments on nonmortgage loans as the change in end-of-month balances on loan accounts. Positive values correspond to net repayment, negative to net borrowing.

We define liquid assets as the sum of deposit account balances and financial securities. Consequently, our measure of net saving in liquid assets has two components. First, we use the change in end-of-month balances on deposit accounts to capture net saving in such accounts. Second, we add the net outflow across all accounts stemming from financial securities trades. Outflows from such trades reflect that the customer has purchased securities, while inflows reflect sales, so net outflows capture net investment. A particular advantage of this approach, as opposed to using the change in the end-of-month value of the portfolio, is that it separates the active net saving component from value changes due to capital gains and losses.

Household Structure.—The population register provided by Statistics Denmark (Statistics Denmark 2019a) contains annual demographic information about the entire Danish population. The data include information about the ages and genders of all individuals and, importantly, the personal ID numbers of spouses (including cohabiting partners) in each calendar year. This enables us to study outcomes at the household level rather than at the individual level where measurement can be biased by invisible intrahousehold effects—if, for example, a spouse purchases more of the consumption goods of the household when unemployed than when employed. The identities of spouses are also needed to identify spousal labor supply responses to job losses. Many couples are not linked to each other in the bank data. Without information on household structure from the population register, these individuals would be treated as separate households.

Bank Relationships.—The Danish Tax Agency collects end-of-year information about all interest-bearing loans and deposits held in Danish banks by Danish residents (Danish Tax Agency 2015). The data is third-party reported by financial institutions, and it contains account-level information about balances as well as a unique identifier for the reporting institution. With this data, we can address a key concern when working with transaction data from a single provider—namely, whether the available data provide a complete picture of the activities of households that may also transact through other banks or intermediaries.

Mortgage Loans.—We use a loan-level dataset collected from Danish mortgage banks by the Danish Ministry of Business and Growth and the Danish central bank and made available to researchers by Statistics Denmark (Statistics Denmark 2018). It provides an end-of-year snapshot of all active mortgage loans to private individuals in Denmark. It contains detailed information about the date of origin, time to maturity, original and outstanding balance, and interest rate on each loan. It also describes the type of loan, including whether it is a fixed- or adjustable-rate loan and whether it is an interest-only loan. Combining the end-of-year snapshot in a given year with that of the previous year, we can detect whether there are any changes to an individual's portfolio of mortgage loans during the calendar year. We use the information on dates of origin for the new loan(s) to determine exactly when this change happens and thus construct a high-frequency dataset with information about mortgage loans held at the end of each month (see online Appendix D for details).

Mass Layoffs.—We use firm-level information about mass layoffs reported by firms to the Danish Agency for Labour Market and Recruitment to isolate involuntary job losses (Danish Agency for Labour Market and Recruitment 2017). These data contain information about the ID of the firm, the extent of the planned layoffs, and the date of reporting to the agency. Through the firm ID, we can link them to the payroll data from the tax agency and thus construct a subsample of individuals who were laid off shortly after their employer reported a planned mass layoff (see online Appendix E for further details).

Background Characteristics.—To construct demographic background variables, we use individual-level data from government administrative registers containing information about annual income and wealth (Statistics Denmark 2019g), education level (Statistics Denmark 2019k), home ownership (Statistics Denmark 2019d), and white-collar or blue-collar status (Statistics Denmark 2019e).[7]

III. Sample Selection and Research Design

We define a job loss event as a situation where the wage payments from the individual's main employer cease and total gross wage income drops below DKr1,000 ($190, as of January 2010). The first month when these conditions are met is defined as the month of the job loss. To focus on transitions into unemployment, we require that the individual receives unemployment benefits or social insurance at some point between months -1 and 3 relative to the month of the job loss and that he or she does not receive early retirement, sickness, or parental leave benefits in this time period. Moreover, in order to identify shocks rather than recurring events, we restrict

[7] We use mapping files from Statistics Denmark (Statistics Denmark 2019c, i, j) to group granular industry, education, and municipality codes in higher-level categories.

attention to individuals who have gross wage income of at least DKr10,000 ($1,920) for at least 18 consecutive months before the job loss and do not return to the same employer within three months after the job loss.[8]

The observation window for the event analysis is 18 months before to 24 months after the month of the job loss. Note that we are interested in how individuals respond to job losses, not how consumption and saving evolve during unemployment spells. Therefore, in contrast to recent papers that focus on the latter question (Ganong and Noel 2019; Gerard and Naritomi 2021), we let individuals stay in the sample after they return to employment. The unit of analysis is individual-by-month, but outcome variables are generally measured at the household level by summing over the adult members.

Our analysis sample consists of individuals born between 1950 and 1979 who experienced a job loss event between July 2010 and December 2015.[9] We focus on stable households by requiring that the individual either stays single or has the same spouse in all of the months in which they enter the analysis. We exclude individuals if they or their spouse bought or sold real estate or if they worked at the same firm as their spouse prior to the job loss. The former restriction is imposed because housing trades are associated with massive financial transactions, making it difficult to isolate the saving and spending responses to the job loss event. The latter restriction is imposed because correlated income shocks stemming from the same employer prevent us from cleanly examining the spousal labor supply effect of job loss.[10]

Finally, to produce our main results, we limit the sample to households who are active customers at the bank. Following previous literature, we define an active customer as a person with at least five spending outflows in each month of the observation window (Ganong and Noel 2019). For couples, we require that both partners are active customers.

Using outcomes based on the account and transaction data of customers in one financial institution raises concerns about whether the sample is representative of the full population and whether one captures the complete set of relevant transactions (Baker 2018). Our combined data make it possible to address these concerns. Table 1 provides summary statistics for individuals in different samples, measured six months before the month of job loss. Column 1 shows that our gross sample of job losers drawn from the full population consists of 66,844 individuals before restricting it to active customers at the bank. Introducing this restriction produces our baseline sample of 10,002 individuals, as shown in column 2. The active customers are, on average, slightly better educated and more likely to be single, work in the public sector, and reside in the capital region than individuals in the gross sample, and they also earn slightly higher incomes. But, overall, the two samples are quite similar in their socioeconomic characteristics.

[8] The administrative registry data do not contain information about whether job separations are the result of quitting or layoffs. Our procedure is designed to narrow in on the subset of job separations that are likely the result of layoffs while maintaining a sample size that allows us to estimate the effect of job loss with a relatively high level of precision. However, we also make use of data about mass layoffs, which occur less frequently, to verify that our results hold in a (much smaller) sample where all separations are almost certainly involuntary layoffs.

[9] The transaction data cover the years 2009–2016, so this sample selection criterion ensures that we observe our key variables for at least 18 months before and 12 months after the job loss event for all individuals in the sample.

[10] In robustness analysis, we show that our results are insensitive to relaxing either of these sample restrictions.

Table 1—Sample Selection and Summary Statistics

	Gross sample (1)	Active customers (baseline sample) (2)	Exclusive customers (3)
Number 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
Homeowner	0.65	0.63	0.59
Annual gross income for person who lost job (DKr)	371,621	394,499	375,019
Share of household bank deposits held at other banks	0.71	0.05	0.00
Share of household retail bank loans held at other banks	0.71	0.11	0.00

Notes: Column 1 shows statistics for the gross sample of job losers drawn from the full population, i.e., with no requirements on customer status at Danske Bank. Column 2 shows statistics for the baseline sample of active customers, i.e., individuals who are customers at the bank and 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 for the following: annual gross income, measured over the calendar year in which month −6 occurs; and shares of household loans and deposits held at other banks, measured at the end of calendar year before month −6. Online Appendix Table A1 provides additional summary statistics for each of the three samples.

The active customers hold a nontrivial share of their deposits (5 percent) and nonmortgage loans (11 percent) with other retail banks. Column 3 shows statistics for a subsample of exclusive customers, defined as active customers who do not have deposits or loans at other retail banks at any time during the observation window. In Section IV, we show that our results are virtually unchanged if we use this subsample instead, alleviating concerns about lack of completeness. The same is true if we instead impose representativeness by reweighting observations in the sample of active customers to match the socioeconomic background characteristics of the gross sample shown in column 1.

To organize our analysis, we start from the simple cash-flow identity stating that the change in a household's account balances over a given period is equal to the difference between inflows to and outflows from the accounts in that same period:

$$\text{(1)} \qquad \textit{Change in account balances} = \textit{inflows} - \textit{outflows}.$$

Each of the terms in equation (1) can be broken down in subcomponents with economically meaningful interpretations. For example, inflows include wage payments to the main person (i.e., the person losing a job) but also wage payments to the spouse and government income transfers, among other things.[11] Replacing each

[11] To be precise, we split inflows in wage payments to the main person, wage payments to the spouse, government transfers, private transfers and other income, proceeds from sales of financial securities, and a residual of uncategorized inflows. Outflows consist of spending, repayments on mortgage debt, purchases of financial

of the terms in equation (1) with their subcomponents, letting Δ denote changes in response to job loss, and rearranging, we get

$$(2)\qquad \underbrace{\begin{array}{l} -\Delta \textit{Wage income, main person} \\ -\Delta \textit{Government transfers} \end{array}}_{\textit{Income loss from job loss}} = \underbrace{\begin{array}{l} \ \Delta \textit{Wage income, spouse} \\ +\ \Delta \textit{Private transfers and other inc.} \\ -\ \Delta \textit{Spending} \\ -\ \Delta \textit{Net saving in liquid assets} \\ -\ \Delta \textit{Nonmortgage loan net repaym.} \\ -\ \Delta \textit{Mortgage loan repayments} \\ +\ \textit{Residual} \end{array}}_{\textit{Compensating responses}}$$

where we have applied the definition of net saving in liquid assets introduced in Section II.[12] The left-hand side of equation (2) is the after-tax income loss for the person experiencing job loss. Our objective is to estimate this and then examine how households respond by estimating each of the compensating responses on the right-hand side except for the residual. The latter is the change in net uncategorized flows in response to job loss. If the compensating responses included in our analysis add up to match the income loss, this will be close to zero, suggesting that our analysis captures all relevant response margins.

We estimate dynamic versions of each of the terms in equation (2) using a standard event-study model for each outcome:

$$(3)\qquad y_{it} = \gamma_t + \delta_i + \sum_h \beta_h \cdot \mathbf{1}\{e_{it} = h\} + \epsilon_{it}.$$

Here, i indexes individuals, t indexes calendar months, γ_t is a year–by–calendar-month fixed effect, δ_i is an individual fixed effect, and e_{it} is event time, defined as distance in months to the month of job loss, with negative values indicating that individual i has not yet lost the job in month t. We include observations up to 18 months before and 24 months after the month of job loss. Identification in this type of model requires two reference categories (see, for example, Dobkin et al. 2018), so we leave out the indicator variables for $h = -18$ and $h = -6$. We normalize all nominal outcomes by measuring them relative to the household's ex ante disposable income, which we define as the average disposable income in months -18 to -3. To limit the influence of extreme outliers, we censor the normalized outcome variables at the 2.5 and 97.5 percentiles within each event month. Standard errors are clustered at the level of the individual to allow for arbitrary forms of heteroskedasticity and autocorrelation across observations for the same person.

securities, and uncategorized outflows. Finally, changes in account balances consist of changes in deposit accounts and changes in loan accounts, corresponding to our measures of net saving in deposit accounts and net repayment of nonmortgage loans, respectively.

[12] Recall that we define this as the sum of net saving in deposit accounts and net saving in financial securities. We measure the former as the change in balances on deposit accounts and the latter as net outflows (outflows minus inflows) associated with securities trades.

The coefficient of interest is β_h, which captures the dynamics of the outcome variable around the time of the job loss. Each coefficient expresses the difference in the normalized outcome in event month h relative to the pre-event level. As summary measures of the total impact on the outcomes over the full observation window, we sum the β_h estimates for months -5 to 24. These sums capture the cumulative net effects on each outcome over the time horizon we study—expressed in multiples of ex ante disposable income—and thus facilitate comparisons of effect sizes across outcomes.[13]

IV. Main Findings: Income Loss and Compensating Responses

Figure 1 shows our main results. Based on the breakdown in equation (2) and the econometric specification in (3), it shows the impact of job loss on monthly income (markers) and the compensating responses (bars) for the average household on a timeline centered around the month of job loss. To ease readability, we pool the compensating responses from mortgage loan repayments and nonmortgage loan net repayments into one category, labeled "borrowing and reduced debt payments."[14] We present the results briefly in this section and provide further analysis of selected responses in the next.

Income Loss.—Starting on the left-hand side of equation (2), we find that job loss has a large effect on the affected person's after-tax wage payouts (the black dots in Figure 1). Wage payouts are higher than normal in the two months before job loss due to sizable severance payments for some individuals but then drop sharply at layoff. The average drop corresponds to about half of the household's ex ante disposable income, reflecting that most households also have income from other sources (such as wage income earned by the spouse). Wage income recovers steadily in the following months, as some individuals return to employment, but never catches up to the predisplacement level within the two-year window of our analysis. In month 24, the gap remains almost half its initial size. This is in line with previous findings of persistent income losses following the transition into unemployment (Jacobson, LaLonde, and Sullivan 1993; Davis and Wachter 2011; Kawano and Lalumia 2015; Flaaen, Shapiro, and Sorkin 2019; Seim 2019). The total cumulated effect on after-tax wage income over the analysis horizon amounts to a loss of seven months of ex ante disposable income (online Appendix Table A2, column 5).

Social insurance provides significant income compensation. The income loss from job loss is much smaller when we take into account the increase in transfers from the government, as illustrated by the red diamonds in Figure 1. Over the full observation window, we estimate that these transfers compensate for two-thirds of the wage loss for the average household. Thus, the total income loss from job

[13] We include the estimates for months -5 to -1 to capture effects taking place before the month of job loss—for example, due to advance notice or severance payments.

[14] Online Appendix Figure A3 shows estimates and confidence intervals from model (3) separately for each of the terms in equation (2) except for the residual. Online Appendix Table A2 reports point estimates and standard errors for key coefficients underlying Figure 1 as well as for cumulative effects over months -5 to 24.

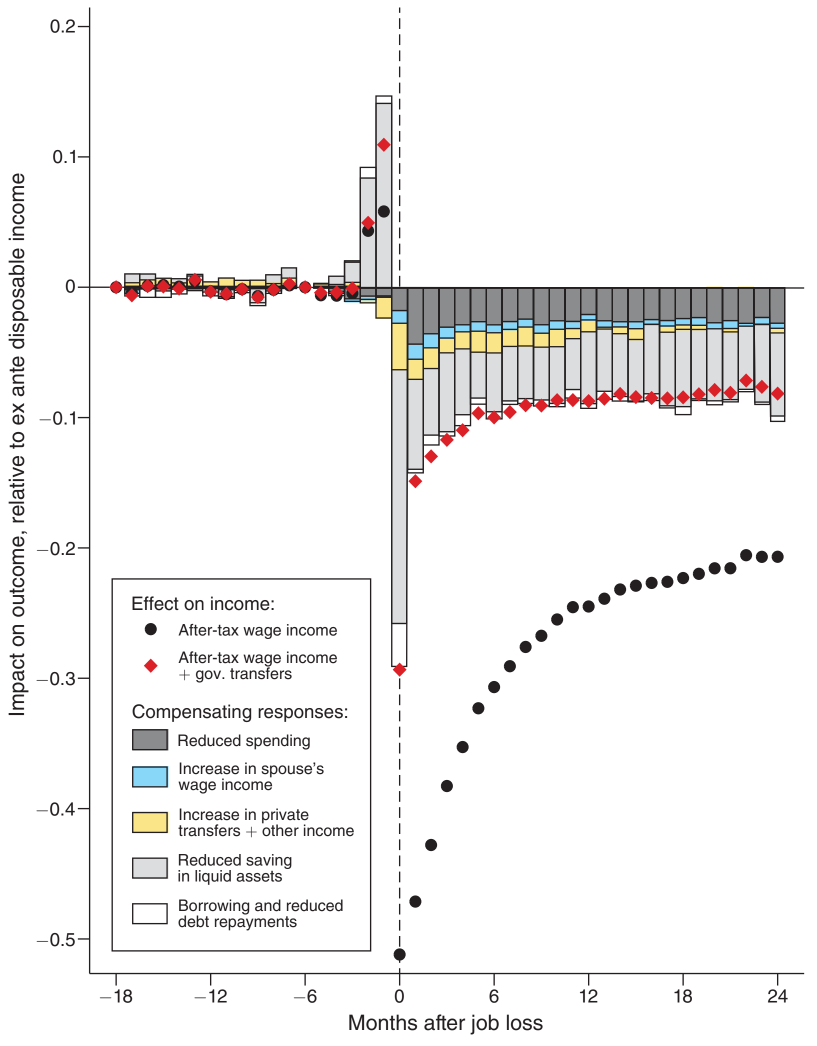

Figure 1. Income, Spending, and Self-Insurance Responses to Job Loss

Notes: The figure shows estimation results from the event-study model (3) of the effects of job loss on a range of outcomes. All outcomes are measured relative to ex ante disposable income and winsorized at the 2.5 and 97.5 percentiles within each event month. Estimates for the effect on income are illustrated by series of shaped markers. The series labeled "after-tax wage income" shows β_h coefficient estimates from a regression with after-tax wage income for the household member who lost their job as the outcome. The series labeled "after-tax wage income + gov. transfers" is the sum of these coefficients and the corresponding ones from a regression with income from government transfers as the outcome. Estimates for compensating responses are shown in bars. We estimate coefficients for each outcome in separate regressions and illustrate the sums of these coefficients by the height of the stacked bars. In calculating these sums, each component is signed so that a negative value indicates a change that contributes to compensating for the loss of income. The series labeled "borrowing and reduced debt repayments" shows the sums of coefficients for two separate outcomes: nonmortgage loan net repayments and mortgage loan repayments. Figure A3 and Table A2 in the online Appendix show, respectively, full dynamics and selected coefficient estimates with standard errors for each separate outcome.

loss, cumulated over the full analysis horizon and accounting for social insurance, is equivalent to about 2.5 months of ex ante disposable income.

Compensating Responses.—Turning to the right-hand side of equation (2), the bars in Figure 1 show how households respond to compensate for this income loss. Starting with household spending, we find a clear negative effect in all 24 months following job loss (black bars). Over the entire period, we estimate that the reduction in spending corresponds to 30 percent of the income loss. This aligns with the finding in the existing literature that the spending response to job loss, while significant, leaves a substantial gap compared to the size of the income loss.

Only a small part of this gap is filled by increases in spousal wage income, as illustrated by the length of the blue bars in Figure 1. Cumulated over the full analysis period, the extra income from this source covers 7 percent of the main person's income loss. The increase is entirely along the intensive margin, with no significant effect on the spouse's employment rate (see online Appendix Figure A4). These results suggest that the added-worker effect provides only a modest degree of insurance against job loss for the average household in our sample.

The effect on private transfers and other income is somewhat stronger. Over the full analysis horizon, such inflows increase by an amount corresponding to 0.2 months of ex ante disposable income, thus compensating for 10 percent of the cumulated income loss. This may reflect informal insurance through gifts and loans from extended family and friends (Andersen, Johannesen, and Sheridan 2020) but can also capture inflows stemming from sales of real assets or consumer durables.

Saving in liquid assets is the most important response margin. Liquid asset accumulation spikes upward just before the job loss (mirroring the increase in income from severance pay), drops drastically at the onset of unemployment, and then stays significantly below predisplacement level throughout the analysis horizon. The cumulated response compensates for 49 percent of the cumulated income loss, which is a significantly larger share than for any other response, economically as well as statistically.[15]

In contrast, we find only a modest impact of job loss on borrowing and debt repayments. The effect is strongly concentrated in month 1 after displacement, where we observe a sizable increase in nonmortgage borrowing (online Appendix Figure A3). Over the full period, the changes in borrowing and debt repayment behavior compensate for less than 5 percent of the income loss.

The joint effect of these compensating responses, illustrated by the height of the stacked bars, matches the income loss almost perfectly. This is true in cumulated terms—the total sum of cumulated responses is just 0.7 percent above the estimated cumulative income loss; see online Appendix Table A2, column 5—but also within nearly all event months. This suggests that our analysis captures all relevant response margins to the income loss associated with job loss.

In summary, we find that lower spending compensates for 30 percent of the income loss over the two-year period following job loss, while household self-insurance makes up for the remaining 70 percent. Self-insurance comes in two forms, each associated with a particular class of behavior: One class involves shifting consumption across time by adjusting saving and debt accumulation; the other involves raising financial

[15] The null that this share is numerically equal to the corresponding share for private transfers and other income (the second-largest response) has a p-value of 0.009 against a two-sided alternative.

flows from other sources to compensate for the income loss. Our results show that the former class is, quantitatively, far more important than the latter for the average person experiencing job loss, primarily due to sizeable adjustments in the accumulation of liquid assets.

Completeness and Representativeness.—Our analysis relies on transaction data from a single commercial bank. This raises potential concerns about whether the data cover all the transactions the households are involved in (*completeness*) and whether the customers of the bank are similar to the population at large (*representativeness*). Table 2 explores how our key estimates change as we alter sample selection criteria and estimation methods to address these concerns. All columns report estimates of cumulative effects over months -5 to 24 relative to the month of job loss. Odd-numbered columns show these effects measured in multiples of ex ante disposable income, while even-numbered columns express them relative to the cumulated income loss.

Columns 1–2 report results for our baseline sample, while columns 3–4 show the corresponding estimates for the smaller subsample of households that are exclusive customers at the bank. Overall, the two sets of results are highly similar. Since exclusive customers do not bank elsewhere, we take this as evidence that our baseline results are not plagued by lack of completeness in the transaction data to any significant extent. Columns 5–6 report results from regressions where the observations in the baseline sample are reweighted to match the demographic characteristics of the gross sample of job losers drawn from the full population.[16] The results are again similar to those shown in columns 1–2 for the baseline sample, suggesting that our main results do not suffer from lack of representativeness.

Further Robustness.—The results are also robust to other potentially important variations of the sample selection criteria. First, as shown in online Appendix Table A3, we can relax the sample restrictions that exclude unstable households and those involved in real estate transactions with no material impact on our main findings. Second, the aim of our analysis is to examine the response to job losses, i.e., involuntary separations. The administrative records do not contain explicit information on whether job separations are voluntary or not from the worker's side. As explained in Section III, we impose restrictions to exclude voluntary resignations, but we cannot rule out that such cases occur in our main analysis. To address this concern, we identify individuals in our sample who lose their job concurrently with mass layoffs at their employer and rerun our analysis on this subsample. Mass-layoff events are identified by exploiting that firms must report directly to the Danish Ministry of Employment when they plan to lay off workers on a large scale (see online Appendix E for details). The results, shown in columns 7–8 of online Appendix Table A3 and further illustrated in online Appendix

[16] The gross sample corresponds to the one shown in column 1 of Table 1. Weights are constructed as the inverse predicted probabilities from a probit regression estimated on this gross sample. The dependent variable is a dummy for belonging to the baseline sample of active bank customers, and the regressors are the demographic characteristics reported in Table 1, i.e., dummy variables for age (five-year intervals), sex, couple, capital region residence, higher education, sector of employment before layoff (seven categories), and home ownership.

Table 2—Representativeness and Completeness

	Cumulated effects, months −5 to 24					
	Baseline		Exclusive customers		Weighted regressions	
	(1)	(2)	(3)	(4)	(5)	(6)
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
[1] Wage income	−6.92		−7.93		−6.47	
	(0.14)		(0.21)		(0.15)	
[2] Government transfers	4.56		5.14		4.32	
	(0.08)		(0.11)		(0.09)	
[3] Income loss (= −[1] − [2])	2.36	100.0%	2.78	100.0%	2.15	100.0%
	(0.14)		(0.20)		(0.14)	
Compensating responses						
[4] Wage income, spouse	0.16	6.6%	0.23	8.2%	0.17	8.0%
	(0.07)	(2.9%)	(0.09)	(3.3%)	(0.09)	(4.0%)
[5] Private transfers and other income	0.23	9.8%	0.27	9.7%	0.20	9.1%
	(0.15)	(6.4%)	(0.21)	(7.4%)	(0.15)	(7.0%)
[6] Spending	−0.72	−30.3%	−1.10	−39.7%	−0.57	−26.4%
	(0.15)	(6.5%)	(0.23)	(8.6%)	(0.16)	(7.4%)
[7] Net saving in liquid assets	−1.16	−49.2%	−1.07	−38.4%	−1.12	−52.1%
	(0.29)	(12.0%)	(0.43)	(15.2%)	(0.31)	(13.8%)
[8] Nonmortgage loan net repayments	−0.04	−1.9%	0.05	1.9%	−0.04	−1.7%
	(0.10)	(4.1%)	(0.14)	(5.0%)	(0.11)	(4.9%)
[9] Mortgage loan repayments	−0.06	−2.7%	−0.05	−1.9%	−0.06	−2.9%
	(0.01)	(0.6%)	(0.02)	(0.6%)	(0.01)	(0.7%)
[10] Total (= [4] + [5] − [6] − [7] − [8] − [9])	2.38	100.7%	2.67	96.0%	2.15	100.2%
	(0.26)	(10.0%)	(0.36)	(12.0%)	(0.27)	(11.2%)
Number of individuals	10,002	10,002	5,224	5,224	10,002	10,002

Notes: The table reports results from analyses aimed at assessing whether lack of representativeness or completeness in our data affect the results. Columns 1–2 show results for our baseline sample and estimation method, columns 3–4 for the subsample of exclusive customers who do not hold accounts at any other Danish bank, and columns 5–6 for regressions where observations are reweighted so that our sample of active customers matches the demographic characteristics of the gross sample shown in column 1 of Table 1. All estimates are based on regressions where the reported outcomes are measured relative to ex ante disposable income. 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 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.

Figure A5, align with our main findings, but standard errors are considerably larger due to the much smaller sample size.

V. Understanding the Compensating Responses

In this section, we take a closer look at the compensating responses to job loss shown in Figure 1 to better understand the behavioral adjustments they represent. We focus on three responses: spending, borrowing and debt repayments, and saving in liquid assets.

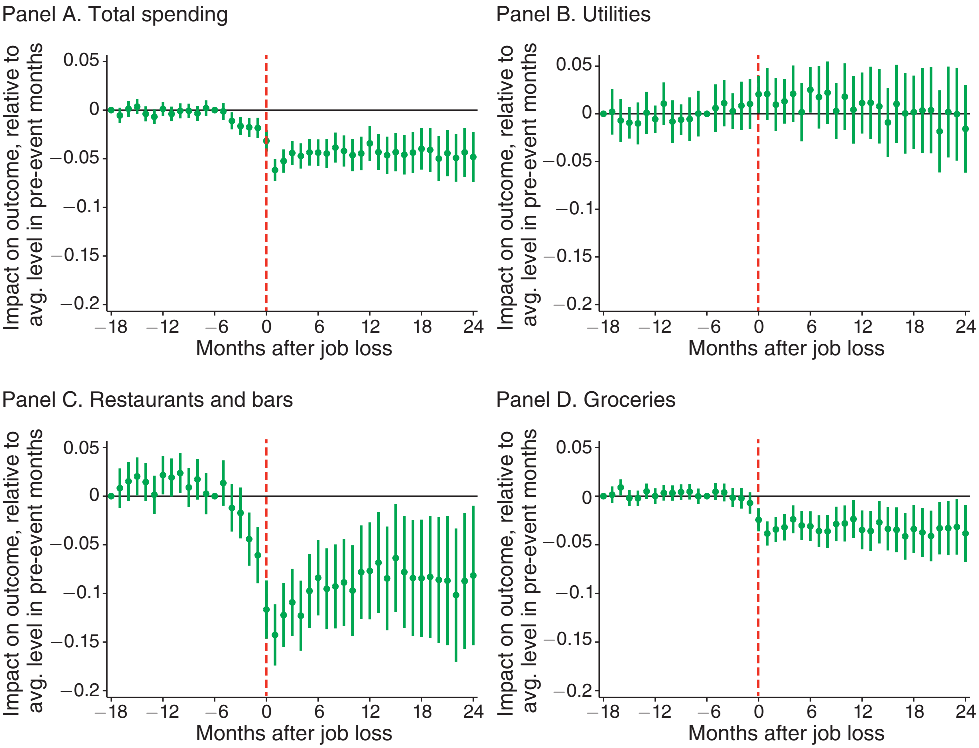

Figure 2. Relative Responses for Total Spending and Selected Subcomponents

Notes: The figure shows estimation results from the event study model (3) of the effects of job loss on selected categories of household spending. Spending categories are defined by Merchant Category Codes, as described in online Appendices A and B. All outcomes are measured relative to their own sample averages in event months −18 and −3 and winsorized at the 2.5 and 97.5 percentiles within each event month. Vertical lines represent 95 percent confidence intervals. Standard errors are estimated allowing for clustering at the level of the individual.

Spending.—In Section IV, we expressed the spending reponse in equivalents of ex ante disposable income, with the aim of comparing it directly with other response margins. Figure 2 shows results where we instead express the responses of both total spending and selected subcategories of expenditure relative to their own pre-event levels. Panel A shows that total spending drops by 6 percent at the time of job loss and then recovers somewhat, hovering at 4–5 percent below the pre-event level.

There is substantial variation across subcategories, however, as shown in panels B–D: In line with theory, we find that households maintain spending on consumption commitments (Chetty and Szeidl 2007, 2016), as proxied by utility bills, but cut down substantially on discretionary luxury goods, as proxied by restaurant and bar spending. In between these extremes, the relative drop in grocery spending is about the same size as for total spending. This suggests that part of the overall spending drop reflects an actual reduction of consumption and not merely self-insurance through postponement of luxury good or durables purchases (Browning and Crossley 2000, 2009).

Figures 1 and 2 both show that the sharp drop in spending at the time of job separation is preceded by a gradual decline in the months just before. To understand this, it is important to note that our analysis centers on the month in which we observe wage income dropping to near zero. In reality, many employees receive notice about being laid off some months in advance, raising the possibility that they start adjusting long before that point. To assess whether this is the case, we exploit the fact that white-collar workers are employed on contracts that secure them at least three months' notice while blue-collar workers are employed on contracts that imply much shorter notice periods, sometimes even as little as one day. Online Appendix Figure A6 shows that while blue-collar workers maintain a roughly constant spending level right until the month of job loss, while-collar workers do indeed start cutting back as early as five months before. This supports the interpretation that the pre-event decline reflects anticipation due to notice periods.

Borrowing and Debt Repayments.—The modest response from borrowing and debt repayment may seem surprising, given that 63 percent of the individuals in our sample are homeowners and that Denmark has a well-developed mortgage market (Campbell 2012). About half of the cumulated response in this category comes from lower payments on mortgage loans (online Appendix Table A2). Figure 3 illustrates that this is driven by a small share of homeowners who convert their mortgage loans to loan types with lower debt service costs—specifically, interest-only loans (panel A) and adjustable-rate loans (panel B)—whereas we find no impact on home equity extraction through mortgage refinancing (panel C). These moderate mortgage responses are consistent with recent evidence in DeFusco and Mondragon (2020) showing that unemployed US citizens have high latent demand for mortgage refinancing but are constrained by their employment status.

Lower net repayments on nonmortgage loans account for the other half of the cumulated response in the category of borrowing and debt repayments. This reflects higher borrowing activity, but also that some individuals fall behind on their scheduled repayments. In support of the latter claim, we find that loan arrears become more prevalent after job loss. From the tax data, we have end-of-year information about arrears on any debt owed to Danish lenders. As shown in online Appendix Figure A7, the incidence of such arrears increases by 0.5 percentage points by the end of the second calendar year following the job loss. The baseline incidence in the population is around 5 percent (Kreiner, Leth-Petersen, and Willerslew-Olsen 2020), implying that the estimated effect amounts to an increase in arrears of about 10 percent.

Saving in Liquid Assets.—The large and persistent negative effect of job loss on net saving in liquid assets shown in Figure 1 reflects two things. First, many households accumulate liquid assets before the month of job loss but stop doing so (or continue at a lower pace) afterward.[17] Second, some households not only stop

[17] Online Appendix Figure A8 shows that the level of net saving in liquid assets is in fact positive before job loss for the average household in our sample. That is, households accumulate assets. Most of this accumulation is in the form of increasing balances on deposit accounts, while net investment in financial securities accounts for just a tiny share.

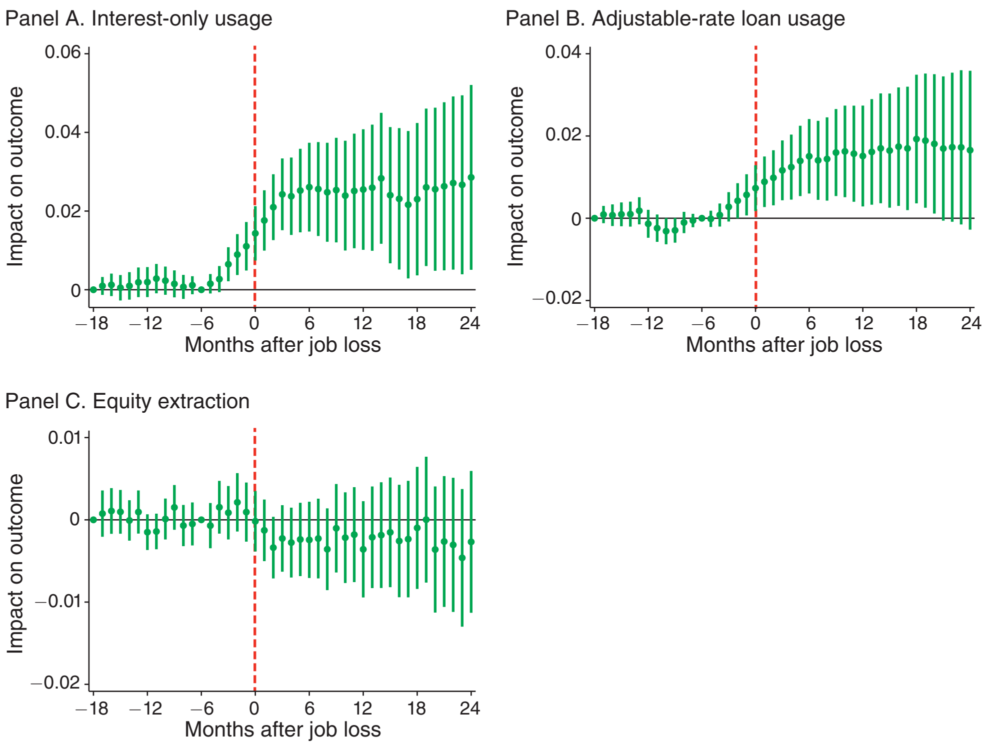

FIGURE 3. MORTGAGE LOAN RESPONSES (MORTGAGORS ONLY)

Notes: The figure shows estimation results from the event-study model (3) of the effects of job loss on mortgage loan outcomes. Panels A and B show results from regressions where the dependent variables are dummies for whether the household has at least one interest-only loan and adjustable-rate loan, respectively. Panel C shows results from a regression where the dependent variable is a dummy for equity extraction. The dummy takes the value 1 if the household replaced an existing mortgage loan with a new one with principal exceeding $(B + 20{,}000)/0.95$, where B is the outstanding balance on the existing loan (DKr). This criterion takes into account that refinancing involves a fixed fee plus a rate loss that is proportional to the principal (typically less than 5 percent). We only include individuals from households with at least one mortgage loan in the estimations. Vertical lines represent 95 percent confidence intervals. Standard errors are estimated allowing for clustering at the level of the individual.

accumulating but start decumulating by running down their stock. To asses the relative importance of these two components, we decompose net saving in liquid assets in a given month as the sum of accumulation and decumulation in that month and estimate equation (3) separately for each.[18] Figure 4 shows the result of this exercise. The large spike in net saving just before job loss reflects a sharp rise in asset accumulation, while the large negative impact on saving in the month of job loss is primarily due to households running down assets. Both components contribute to the negative impact on net saving in subsequent months, but with lower accumulation gradually taking a larger role.

[18] More precisely, we use the following decomposition of net saving in liquid assets: $Netsaving = Netsaving \cdot \mathbf{1}\{Netsaving \geq 0\} + Netsaving \cdot \mathbf{1}\{Netsaving < 0\}$. The first term represents liquid asset accumulation; the second term represents decumulation.

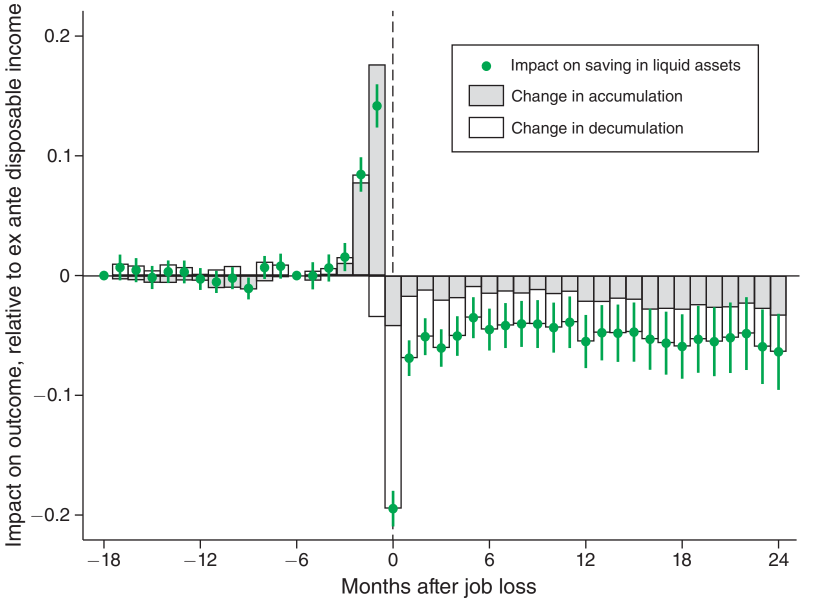

Figure 4. Impact of Job Loss on Net Saving in Liquid Assets: Accumulation versus Decumulation

Notes: The figure shows coefficient estimates from the event study model (3) with net saving in liquid assets as the outcome. Green dots illustrate the change in total net saving relative to the omitted categories, corresponding to the gray bars in Figure 1. The stacked bars decompose this change on contributions from lower asset accumulation and increased asset decumulation. The outcome variables used to construct these bars are net saving in liquid assets multiplied with indicator variables for positive and negative net saving, respectively. The dependent variables are measured relative to ex ante disposable income and winsorized at the 2.5 and 97.5 percentiles within each event month. Vertical lines represent 95 percent confidence intervals. Standard errors are estimated allowing for clustering at the level of the individual.

The sharp increase in asset accumulation just before job loss is a striking feature in both Figure 1 and Figure 4. As we have already alluded to, the source of this spike is severance payments paid to a subset of the households in our sample. To show this more explicitly, we define individuals as receiving sizeable severance payments if their income in either of the two months preceding the job separation is at least 50 percent above their average income in the pre-event months. We then do a split-sample analysis based on this criterion. Unlike in our main analysis underlying Figure 1—but similar to, e.g., Gerard and Naritomi (2021)—we now only keep individuals in the sample for as long as they remain unemployed after having experienced job loss. This eliminates any mechanical effects from differences in the average duration of unemployment between individuals with and without severance payments.

The results of this analysis are displayed in Figure 5. Panel A shows that, apart from the highly visible effect of severance payments just before the time of separation, the income shock associated with job loss is similar for the two groups. However, as shown in panel B, the households who receive severance pay increase spending just before job loss, while those without severance pay do not.[19] Both

[19]This finding parallels the results of Gerard and Naritomi (2021), who find that displaced workers in Brazil increase spending at the time of layoff. They tie this to the fact that most of the workers in their sample receive a

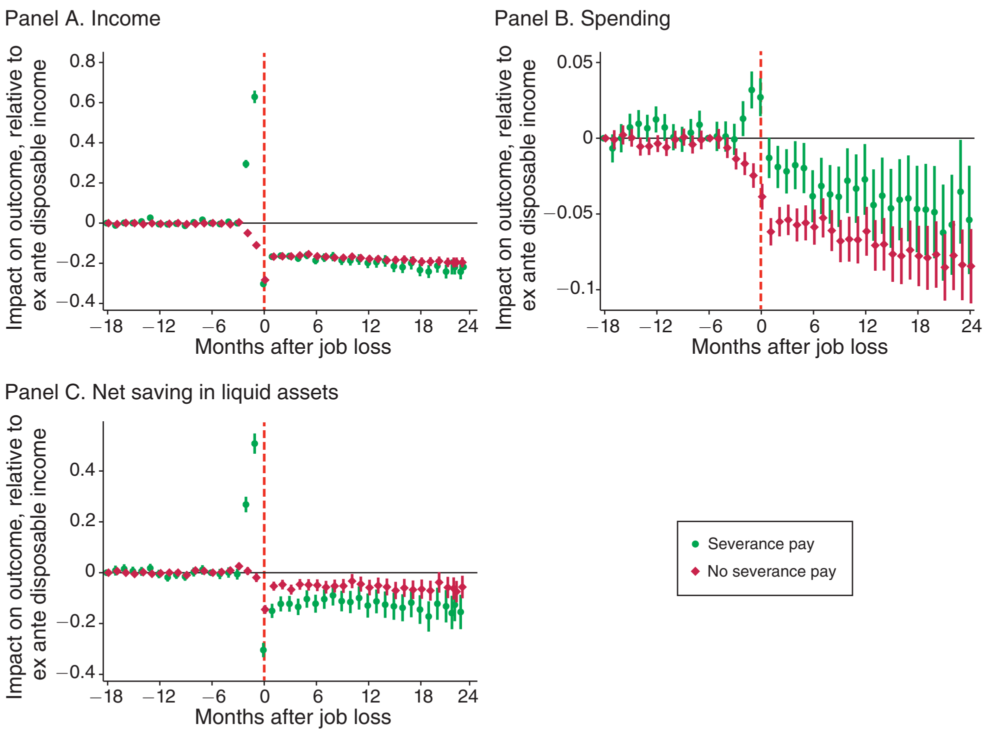

Figure 5. Income, Spending, and Net Saving in Liquid Assets—Severance Pay versus No Severance Pay

Notes: The figure shows estimation results from the event-study model (3) of the effects of job loss on income, spending, and net saving in liquid assets. All outcomes are measured relative to ex ante disposable income and winsorized at the 2.5 and 97.5 percentiles within each event month. The sample is a dynamic sample of individuals who stay unemployed. In event months -18 to 0, this includes everyone in the baseline sample. For event month $t > 0$, it includes those who have not returned to employment at any point between month 0 and month t. Employment status is defined as having gross wage income above DKr10,000 (at January 2010 price levels). Panel A shows results for income, defined as the sum of wage income for the person experiencing job loss and government transfers for the household. Panels B and C show results for household spending and net saving in liquid assets, respectively. Each panel shows results for two subsamples: *Severance pay* denotes individuals whose income in month -1 or -2 is at least 50 percent above the average in the pre-event months. *No severance pay* denotes individuals who do not satisfy this criterion. Vertical lines represent 95 percent confidence intervals. Standard errors are estimated allowing for clustering at the level of the individual.

groups reduce spending after separation, but the severance payment group stays considerably closer to the pre-event level throughout the two-year analysis horizon. Panel C illustrates what makes this possible: After the large injection of liquid funds just before the month of job loss, the households receiving severance pay reduce net saving by much more than other households in our sample. These findings suggest that the liquidity boost that severance payments provide serves as a buffer to mitigate the consequences of job loss for spending.

large lump-sum payment in the form of government-mandated severance pay when they are laid off.

VI. Heterogeneity Analysis

The results in Figure 1 illustrate the income loss and compensating responses for the average person experiencing job loss. These results may mask considerable heterogeneity, however, as households differ in the choice sets they face following job loss. First, the shadow price of spending—i.e., the marginal cost of raising an extra dollar to sustain spending despite the income loss—varies due to differences in balance sheets, access to credit markets, and opportunities to raise income from alternative resources (Landais and Spinnewijn 2021). For example, households with limited access to liquidity face a higher cost of smoothing through adjustments to borrowing and saving than those with plenty of liquid assets, and singles have fewer opportunities for raising income from other sources than married or cohabiting individuals who can compensate for the earnings loss by letting the partner take extra jobs or shifts. Second, the marginal cost of reducing spending varies due to differences in the composition of spending. For example, households who primarily spend their money on necessities such as food likely face a high marginal utility cost of cutting back.

To investigate how such differences in costs and opportunities shape the way households cope with job loss, we split the sample by four dimensions: liquid asset holdings, grocery budget share, marital status, and age. The latter split is motivated by the fact that many of the characteristics mentioned above vary systematically over the life cycle, suggesting that responses may differ between young and old households.[20] We then estimate equation (3) for each response margin within each subsample.

Table 3 shows the results of these analyses. As in Table 2, we focus on cumulated effects over months -5 to 24. Refining the breakdown in equation (2), we split the cumulated wage income loss into two parts: the loss of the wage income that the person had before losing the job minus the wage income accumulated from new jobs. The first term expresses the cumulated wage loss that the person would experience by staying unemployed throughout the full analysis, while the second term expresses how much the individual recovers by finding new employment. This decomposition allows us to analyze whether some groups of individuals are more succesful than others in replacing their lost wage income—for example, by searching harder for new jobs—so that their realized income loss ends up being smaller.[21]

High versus Low Liquid Assets.—The results in previous sections suggest that the amount of liquid assets held before job loss is an important determinant of the subsequent responses. To show this more directly, we follow Zeldes (1989) and Leth-Petersen (2010) and split the sample by whether the household had liquid assets corresponding to two months' worth of ex ante disposable income before

[20] We report descriptive statistics for each subsample in online Appendix Table A4.

[21] In the notation of equation (2), we define $-\Delta \textit{Wage income, main person} \equiv -\Delta \textit{Wage income, lost job} - \Delta \textit{Wage income, new jobs}$. We estimate the two terms on the right-hand side by splitting the main person's wage income in each month into wage income from the old job (i.e., the one lost in month 0) and wage income from new jobs and then estimating model 3 separately for each component.

Table 3—Heterogeneity in Responses to Job Loss

	Cumulative effects, months −5 to 24							
Observations	Low liquid assets 196,961		High liquid assets 154,339		Low groceries spending share 210,198		High groceries spending share 209,416	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
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 income from lost job	−14.18		−13.87		−14.71		−12.91	
	(0.25)		(0.25)		(0.21)		(0.19)	
[2] Wage income from new jobs	7.25		6.58		7.08		6.75	
	(0.11)		(0.14)		(0.10)		(0.09)	
[3] Government transfers	4.71		4.36		5.07		4.02	
	(0.13)		(0.15)		(0.11)		(0.11)	
[4] Income loss (= −[1] − [2] − [3])	2.21	100.0%	2.93	100.0%	2.57	100.0%	2.14	100.0%
	(0.24)		(0.25)		(0.21)		(0.19)	
Compensating responses								
[5] Wage income, spouse	0.14	6.3%	0.24	8.3%	0.01	0.3%	0.30	14.1%
	(0.12)	(5.6%)	(0.14)	(4.7%)	(0.09)	(3.5%)	(0.12)	(5.3%)
[6] Private transfers and other income	0.49	22.1%	−0.07	−2.3%	−0.07	−2.7%	0.55	25.6%
	(0.24)	(11.1%)	(0.29)	(10.1%)	(0.23)	(9.0%)	(0.20)	(9.3%)
[7] Spending	−0.91	−40.9%	−0.32	−10.8%	−1.00	−39.0%	−0.41	−19.4%
	(0.25)	(12.1%)	(0.28)	(9.6%)	(0.22)	(9.2%)	(0.19)	(9.0%)
[8] Net saving in liquid assets	−0.69	−31.2%	−1.91	−65.4%	−1.55	−60.3%	−0.77	−36.1%
	(0.44)	(20.2%)	(0.63)	(20.7%)	(0.42)	(16.5%)	(0.40)	(18.4%)
[9] Nonmortgage loan net repayments	−0.05	−2.2%	−0.10	−3.5%	−0.09	−3.5%	0.00	0.1%
	(0.17)	(7.9%)	(0.16)	(5.6%)	(0.14)	(5.4%)	(0.14)	(6.7%)
[10] Mortgage loan repayments	−0.05	−2.3%	−0.10	−3.3%	−0.06	−2.3%	−0.07	−3.4%
	(0.02)	(1.0%)	(0.03)	(0.9%)	(0.02)	(0.7%)	(0.02)	(0.9%)
[11] Total (= [5] + [6] − [7] − [8] − [9] − [10])	2.32	104.9%	2.60	89.0%	2.64	102.7%	2.10	98.5%
	(0.44)	(18.0%)	(0.55)	(17.3%)	(0.40)	(14.7%)	(0.36)	(15.7%)

(*Continued*)

they lost their job.[22] The results are reported in columns 1–4 of Table 3. Job loss has a significant negative impact on the household budget in both subsamples, equivalent to a loss of about 2–3 months of ex ante disposable income over our analysis horizon. For households with high levels of liquid assets, lower net saving in such assets is by far the most important response, compensating for about 65 percent of the income loss, while lower spending only accounts for about 10 percent. In contrast, households with low levels of liquid assets cannot reduce their saving to

[22] In practice, we split the sample by the ratio of liquid assets to ex ante disposable income, lagged by 25 months. Splitting the sample by the level of liquid assets in a particular event month would produce mechanical differences due to mean reversion. By using a lag of 25 months consistently across all event months, we avoid this problem while making sure that the split is always based on an ex ante value. Essentially, identification comes from comparing outcomes within a given calendar month across individuals who all had either high or low liquid assets 25 months earlier but lost their jobs at different points in time after that (while also controlling for individual fixed effects).

Table 3—Heterogeneity in Responses to Job Loss (*continued*)

	Cumulative effects, months −5 to 24							
Observations	Single 171,535		Married or cohabiting 248,079		Young 203,043		Old 216,571	
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
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 income from lost job	−19.15		−10.18		−13.80		−13.88	
	(0.23)		(0.15)		(0.21)		(0.20)	
[2] Wage income from new jobs	8.46		5.86		7.57		6.21	
	(0.13)		(0.07)		(0.10)		(0.08)	
[3] Government transfers	7.13		2.78		4.22		4.94	
	(0.13)		(0.09)		(0.11)		(0.11)	
[4] Income loss (= −[1] − [2] − [3])	3.56	100.0%	1.54	100.0%	2.00	100.0%	2.73	100.0%
	(0.24)		(0.18)		(0.21)		(0.19)	
Compensating responses								
[5] Wage income, spouse	0.00	0.0%	0.26	17.0%	0.16	8.2%	0.13	4.7%
			(0.12)	(7.3%)	(0.11)	(5.5%)	(0.10)	(3.5%)
[6] Private transfers and other income	0.63	17.6%	−0.04	−2.7%	0.23	11.4%	0.23	8.4%
	(0.22)	(6.1%)	(0.21)	(14.0%)	(0.23)	(11.4%)	(0.21)	(7.5%)
[7] Spending	−1.27	−35.6%	−0.33	−21.8%	−0.91	−45.7%	−0.59	−21.5%
	(0.25)	(7.5%)	(0.17)	(11.9%)	(0.22)	(11.5%)	(0.19)	(7.2%)
[8] Net saving in liquid assets	−1.88	−52.8%	−0.68	−44.2%	−0.54	−27.0%	−1.74	−63.6%
	(0.43)	(11.9%)	(0.41)	(26.6%)	(0.39)	(19.5%)	(0.44)	(15.7%)
[9] Nonmortgage loan net repayments	0.01	0.2%	−0.08	−5.3%	−0.03	−1.7%	−0.05	−2.0%
	(0.14)	(4.0%)	(0.13)	(8.3%)	(0.15)	(7.6%)	(0.13)	(4.7%)
[10] Mortgage loan repayments	−0.04	−1.2%	−0.08	−5.2%	−0.08	−4.1%	−0.05	−1.8%
	(0.01)	(0.4%)	(0.02)	(1.3%)	(0.02)	(1.1%)	(0.02)	(0.7%)
[11] Total (= [5] + [6] − [7] − [8] − [9] − [10])	3.81	107.0%	1.40	90.7%	1.96	98.1%	2.79	102.1%
	(0.40)	(10.5%)	(0.36)	(22.3%)	(0.37)	(17.1%)	(0.40)	(13.4%)

Notes: The table shows cumulated effects of job loss for various subsamples. Columns 1–4 show results for subsamples defined by whether or not the household held liquid assets worth at least two months of ex ante disposable income 25 months earlier. Lagging the value of liquid assets by 25 months means losing observations before February 2011. Columns 5–8 show results subsamples defined by 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. Columns 9–12 show results for singles versus married or cohabiting individuals. Columns 13–16 show results for individuals below versus above 47 years of age at the time of job loss (the median value in the sample). *Wage income from lost job* is defined as all wage income before the month of job loss. *Wage income from new jobs* is equal to all wage income in and after that month. 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 β_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.

the same extent and are only able to compensate for about 30 percent of the income loss through this channel, while spending cuts cover about 40 percent. These findings support the conclusion that access to liquid assets is important for household responses to job loss. Households who enter the job loss event with plenty of liquidity use it to shift spending across time, mitigating the impact on current consumption. Liquidity-constrained households do not have the same option and reduce spending more.

High versus Low Grocery Spending Share.—Columns 5–8 split the households by how much of their total spending in the pre-event months goes to grocery purchases. A high ex ante grocery spending share indicates that the household already devoted a large fraction of its budget to necessities before job loss, suggesting that the marginal disutility of cutting spending is high. We do indeed find that reduced spending accounts for a smaller share of the income loss for households with a high ex ante grocery spending share (19 percent of income loss) than for those with a low share (39 percent of income loss). Interestingly, compensation from reduced saving in liquid assets is also relatively moderate for households in the former group—due to the fact that they have few liquid assets before job loss; see online Appendix Table A4—whereas they get compensation about twice as high from spousal wage income (14 percent of income loss) and increases in private transfers and other income (26 percent of income loss) as the average household. These results suggest that while spending cuts and reduced saving are, overall, the most important response margins, households that are already on a tight budget with limited liquidity available before job loss go to greater lengths to replace the lost wage income with inflows from other sources.[23]

Singles versus Married or Cohabiting.—Columns 9–12 split the sample by marital status at the time of job loss. The first thing to note is that the income loss—when measured relative to ex ante disposable income—is much larger for singles (3.6 months of ex ante disposable income) than for married or cohabiting individuals (1.5 months of ex ante disposable income). This reflects that losing a job has a much larger effect on the total household budget when there is only one adult. Viewed this way, the results highlight that spouses can insure each other to a significant extent by simply pooling their resources. On top of that comes the added-worker effect through increased spousal wage income, which accounts for 17 percent of the income loss for married or cohabiting individuals and, by construction, nothing for singles. For spending, we find a larger decline for singles than for married or cohabiting individuals, both when measured relative to ex ante disposable income and when expressed as a share of the income loss.

Young versus Old.—Columns 13–16 split the sample by whether the person affected by job loss is above 47 years old when it occurs. The income loss associated with job loss is larger for the old (2.7 months of ex ante disposable income) than for the young (2.0 months of ex ante disposable income). The breakdown in

[23] Online Appendix Table A5 reports results from a more granular heterogeneity analysis where we split the sample in four based on the 2×2 interaction of high versus low liquid assets and high versus low ex ante grocery spending share. The point estimates suggest that the high levels of compensation from spousal wage income and private transfers are indeed driven by those who have a high grocery spending share and few liquid assets, but standard errors are large due to the limited number of observations in each subsample.

rows 1–3 reveals that this is because the young accumulate more from new jobs. But despite their faster return to employment, the young reduce spending much more than the old. To understand this, we note that the old own more liquid assets than the young (see online Appendix Table A4). And, indeed, the compensating response from reduced net saving in such assets is more than twice as large for the old, as shown in row 8 of Table 3.

Summarizing, the results in this section demonstrate that the reponses to job loss vary considerably, and in intuitive ways: Households with better opportunities for self-insuring through a particular channel tend to use that channel more and, consequently, cut back less on spending when one of their members loses a job. Households who face higher utility costs of reducing spending also cut back less and instead raise income from alternative sources.

VII. Concluding Remarks

There is great interest in how households cope financially with job loss. The literature has proposed a range of self-insurance mechanisms, but little is known about their relative importance. This paper quantifies the importance of all empirically relevant self-insurance responses to job loss using transaction data from a major Danish bank merged with data from government administrative registers containing information about employment, household composition, bank connections, and more.

We document a significant reduction in disposable income following job loss. Over a two-year period, about 30 percent of the income loss is accommodated by a reduction in spending for the average job loser. The remaining 70 percent reflects self-insurance, and the single most important self-insurance channel is adjustment of liquid savings, which amounts to almost 50 percent of the income loss.

The self-insurance responses to job loss studied in this paper fall into two broad classes: first, pure consumption-smoothing responses that allow consumption to be moved forward in time without changing overall consumption possibilities. This includes reduced saving in liquid assets and increased borrowing. The second class is responses that mitigate the impact of the income shock by expanding the household's overall consumption possibilities. This includes increases in spousal labor supply and private transfers from family or friends. We show that both classes of self-insurance responses exist in our data, and we document differences in how job losers self-insure that plausibly reflect differences in the costs of employing different response margins. However, for the average person affected by job loss, consumption-smoothing responses—in particular, saving in liquid assets—are by far the most important class of responses. Our findings suggest that simple consumption-savings models incorporating a liquid asset can go far in capturing the most important aspects of household's responses to job loss.

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