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Expectations and Household Spending

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Expectations and Household Spending

Abstract

We estimate the effect of expectations about unemployment on household spending using high-frequency panel data from the RAND American Life Panel. The data were collected during the Great Recession and its aftermath, a time of great economic uncertainty. We use monthly data both on total household spending and on subcategories of spending. We find that changes in total spending made in response to changes in the chances of becoming unemployed are difficult to detect empirically. This is because many categories of spending, such as rent, utilities, and car payments, tend to be fixed from month to month. Nevertheless, when studying subcategories of spending that are more easily adjusted in the short-term, we find significant effects. For example, in response to an increase from 0 to 1 in the probability of becoming unemployed, we estimate that households reduce spending on clothing by about 14%, dining out and other entertainment by 11%, and personal care by 12%.

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Introduction

Standard versions of the life-cycle model imply that a rational and farsighted individual will seek to smooth consumption, or, more precisely, its marginal utility, subject to an intertemporal budget constraint. However, unexpected exogenous wealth shocks will lead to subsequent consumption changes, whereby the individual spreads the required adjustment over her entire remaining life. That is, *ex post* consumption will not be smooth. Because of declining marginal utility such jumps in consumption result in lower total lifetime utility than would have been the case had consumption been smooth.

To reduce the harm to utility caused by a large reduction in consumption, an individual operating in an uncertain environment should build up a stock of buffer savings to moderate a consumption reduction required by a wealth shock. A prominent example of a lifetime wealth shock is unemployment, which typically results in a loss of substantial earnings, not just for the duration of the unemployment spell, but also in the years following the unemployment when workers tend to have lower earnings than they would have had otherwise (von Wachter et al, 2013). Thus, individuals who persistently face a high likelihood of unemployment should build up buffer stock savings to reduce the loss of utility that would result from unemployment. To accomplish this, they would reduce current consumption to achieve higher consumption in the future, especially in times of low or no income.

Although economic theory suggests such a response, little is known about the effect of expectations on household spending decisions because of a lack of appropriate data. To shed light on this issue empirically, one needs longitudinal data on individuals' expectations and on household spending, ideally with sufficient detail to study categories of spending as well as totals. We have collected such data in the Financial Crisis Surveys that we fielded in the RAND American Life Panel, and, indeed, we found suggestive evidence of this in the first ALP Financial Crisis Survey fielded in early November 2008.

Lehman Brothers had collapsed in September of that year, stock markets had lost about 37% from a year earlier (17% in the month of October 2008 alone), and house prices had decreased by 18% according to the Case-Shiller index. However, the effect of the Great Recession had not yet fully unfolded. Stock prices would continue to decline until March, 2009; housing prices would fall another 10%; and the unemployment rate would increase from 6.6% in October 2008 to 10.0 in October 2009%.

At the time of the first survey (early November 2008), 73 percent of households reported they had reduced spending because of the economic crisis. It seems likely, however, that some of this reduction was not due to real effects: stock ownership is not widespread; the unemployment rate had risen only modestly, and many parts of the country had experienced little decline in housing prices by November 2008. The widespread reduction in spending suggests that something other than the real effects of wealth or income loss prompted households to reduce spending. The most likely explanation is that people's expectations for the future had changed.

In November 2008, we asked respondents by how much they had reduced spending in response to the economic crisis. The answers suggested very large reductions, but research has shown that it is difficult for individuals to provide an estimate of their total spending,[1] let alone to estimate the change in spending. To investigate responses in household spending more reliably, we established a monthly interview schedule for the ALP Financial Crisis Surveys starting in May 2009 and included a module to elicit the details of household spending. This had the advantage of reducing recall error in measures of spending. It also permitted detailed sequencing of events and their consequences.

Unemployment rates peaked at 10.0 percent in October 2009 and remained above 9 percent until October 2011. Unemployment hit not just low-skilled workers but affected workers across a much

[1] For example, Hurd et al. (1998) found that a single question about total spending compared with many questions about detailed categories resulted in an underestimate of about 27%.

wider spectrum than in prior recessions. So the threat of unemployment during the downturn and in its aftermath was a great source of uncertainty and posed a threat to future consumption for a sizeable fraction of the population.

To obtain an idea about the magnitude of a change in spending in response to a change in the probability of unemployment, we analyzed a simple two-period life-cycle model with a variable probability of unemployment in the second period. The model solution predicts that as the probability of unemployment in the second period increases, the level of spending in the first period decreases. The amount of the reduction will vary by loss of earnings during the period of unemployment, but it could be large enough to be discernible in data. For example, if the probability of unemployment in the second period increases from 10% to 20%, the reduction in consumption in the first period (in context of constant relative risk aversion utility) is 16%.

To estimate the effect of the risk of unemployment on spending, we need a widespread shock to the probability of unemployment. In a steady environment where some individuals face a persistently higher risk of unemployment than others, the former group will have previously adjusted their spending to build up buffer stock savings so that current spending will be only moderately depressed. Thus, in cross-section, the variation in spending across individuals who have differing probabilities of unemployment will be less than the variation that would result from a shock to expectations. To estimate the pure expectation effect requires panel data collected over a period of time with (large) changes in the probability of unemployment induced by some exogenous event.

The Great Recession of late 2008 and early 2009 and the economically volatile environment that followed provide such an analytical opportunity. The Great Recession was a period of a relatively rapid increase in unemployment, from less than 6 percent in the summer of 2008 to 10 percent in the autumn of 2009. The shock was likely unanticipated; indeed, for nearly five years beforehand, the U.S.

unemployment rate had not reached six percent. Because of the uneven progression of unemployment across industries and occupations, the subjective probability of unemployment varied across individuals as well as over time. We found that the average subjective probability of unemployment in “protective services” was 10%, whereas it was 25% in “construction and extraction.”

To assess how changes in subjective probability of future unemployment can affect changes in current spending, we also need data on total spending and spending by category. We need data on spending by category because some changes in spending, such as that on dining out, are easier to make than other changes in spending, such as that on mortgage payments. In prior work, we found that some categories of spending such as dining out and clothing, respond quickly to actual unemployment, whereas others such as mortgages respond very little (Hurd and Rohwedder, 2013).

Although much previous research has examined expectations in general, we know of practically no empirical research that links expectations as measured by subjective probabilities to spending at the micro level.[2] The large observable changes in the economic environment induced by the Great Recession provide opportunities to learn how revisions of expectations lead to changes in behavior, in particular spending.

Data: The RAND American Life Panel

Our data on employment, expectations, spending and income throughout the time of the Great Recession come from the RAND American Life Panel (ALP).

[2] Stephens (2001) studied the effect of unemployment expectations on food spending and found none. We have found, however, that categories of spending are affected differentially by economic shocks. Furthermore, the shocks accompanying the Great Recession were much larger than in prior recessions, increasing the likelihood of detecting an effect.

The ALP (https://mmic.rand.org/alp) is an ongoing Internet panel run by RAND Labor and Population. At recruitment into the panel, those who report not having access to the Internet at the time are provided with a Web TV (www.webtv.com/pc/), including an Internet access subscription with an e-mail account. As a result, the total sample does not suffer from bias due to a lack of Internet access. Interview data are reweighted to match CPS distributions on demographic characteristics and income. Response rates of approximately 80% for a survey of recruited panel members are achieved by compensating respondents according to interview length.

ALP Financial Crisis Surveys

The Financial Crisis Surveys

The very large stock market declines in October 2008 prompted our first data collection. We designed a survey that was administered to the ALP in November 2008. The survey covered a broad range of topics including: various dimensions of life satisfaction; self-reported health measures and indicators of affect; labor force status; retirement expectations; recent actual job loss and chances of future job loss; housing; financial help (received and given and expectations about these); stock ownership and value (including recent losses); recent stock transactions (actual and expected over the next 6 months); expectations about future stock market returns (one year ahead, 10 years ahead); spending changes; credit card balances and changes in the amounts carried over; impact of the financial crisis on retirement savings; and expectations about future asset accumulation. We followed up with a second longitudinal interview in late February 2009 covering approximately the same topics.

Beginning with the May 2009 interview, we established a monthly interview schedule to collect high-quality, high-frequency data on spending, and to collect data at high frequency on items such as employment, satisfaction, mood, affect and expectations. An objective was to permit detailed sequencing of events and their consequences.[3]

In this research, we use 42 waves of ALP data, from October 2009 to April 2013.

Sample

In November 2008, the ALP had about 2,500 households. We recruited all these into our surveys on the financial crisis. We added a small refresher sample of about 400 households in November 2011, and a larger refresher sample of about 1,500 households in October and November of 2012.

Measurement of spending

We used two designs in our survey. Our initial design was to ask about most categories every month, but to ask about less frequently purchased items only every three months. Each month we asked about spending in 26 categories that are purchased at high to middle frequency. Then, every three months, we asked about the purchase over the past three months of 11 less frequently purchased categories, and about seven big-ticket items. With a few minor exclusions, the total of the three monthly surveys and the quarterly survey add to total spending over the quarter. See the Appendix for the full list of categories and which were asked every month and which were asked every three months.

In November 2011, we introduced another design that asked about every spending category every month. The list of categories remained the same. This alternative design was administered to half the existing sample at the time (assigned at random). The refresher samples of November 2011 and October/November 2012 were also assigned to this alternative design.

[3] To further reduce recall error the survey is only available to respondents for the first 10 days of each month except when the first day of the month falls on a weekend. Then the schedule is shifted by a day or two to accommodate staff work schedules.

As a result, we have monthly observations on all categories of spending for the refresher sample of November 2011 for 19 consecutive waves (October 2011 through April 2013), and for the refresher sample of October/November 2012 for 7 consecutive waves (October/November 2012 through April 2013). For the whole sample, we have monthly observations on the subset of more frequently purchased categories of spending (26 monthly items) covering the period May 2009 through April 2013 or 48 consecutive waves. This subset of spending categories covers approximately 60% of total spending.

A major innovation of the ALP was the development of a "reconciliation" screen. Outliers are a problem in self-administered data collection such as Internet interviewing, because there is no interviewer to question extreme values that may arise due to typos. Therefore, we designed a new strategy for the ALP to help reign in outliers. Following the queries about spending last month on the 26 items, we presented the respondent with a summary table which listed the responses and added them to produce the implied monthly spending total. The respondent was invited to review and edit any items. This produced two very favorable results. Most importantly, it sharply reduced outliers, in turn reducing standard errors for total spending as constructed through the sum of these 26 spending categories. It also gave respondents the opportunity to improve the accuracy of their entries, including previously missing entries, further reducing data noise. Another reconciliation screen followed the spending questions about the less frequently purchased items.[4]

We compared the ALP measure of total spending with the measure from the Consumer Expenditure Survey (CE). The CE has the most authoritative survey measure of spending at the household level, and it aims for a complete measure of household spending (although in much greater

[4] For those who were asked about all spending categories every month the reconciliation screen displayed all spending entries and invited the respondent to review and edit any entries.

detail) using similar methods to ALP. The following table shows the comparison for 2010 and 2011. For ALP, we calculate spending over a year by summing all 26 monthly spending items from the 12 monthly surveys, and the quarterly reported spending items from the quarterly surveys referring to 2010. Average spending in 2010 as reported in the CE was $42,736.[5] Average weighted spending in the ALP was quite close at $42,355 or 99.1% of CE spending. In 2011, ALP spending was 101.4% of CE spending. The similarity of these levels helps to validate our method of measuring spending, and it also shows that it is possible to capture the same amount of spending as in the CE using many fewer categories of spending and, therefore, imposing substantially less respondent burden and cost.

Comparison of ALP and CE measures for total household spending

	ALP	**CE**	**ALP spending as % of CE spending**
2010	42,355	42,736	99.11
2011	44,915	44,281	101.43

ALP sample: restricted to respondents who completed the spending module in all 3 waves pertaining to one quarter. Population averages for one year are computed as the sum of the population averages for each quarter of the year. Respondents are not required to have completed all four quarters in a year to enter the computations of average spending in a quarter.

Measurement of subjective probabilities

Our measures of expectations are elicited in the form of subjective probabilities. They have substantial predictive power for actual outcomes, and their validity has been established by considerable research (Hurd, 2009). The Financial Crisis Surveys in the RAND American Life Panel (ALP) have a number of questions about subjective probabilities over many waves. We assessed expectations about unemployment in the following way:

[5] We excluded from the CE published total for 2010 outlays for "Personal Insurance and Pensions," because we consider contributions to Social Security and pensions part of savings rather than spending. We also exclude life and other personal insurance payments because, except for insurance company profit, they represent transfers from one household to another.

Sometimes people are permanently laid off from jobs that they want to keep. On a scale from 0 percent to 100 percent where '0' means that you think there is absolutely no chance, and '100' means that you think the event is absolutely sure to happen, what are the chances that you will lose your job during the next 12 months?

This question was asked every month in all Financial Crisis Surveys.

Measurement of income

The ALP asked respondents their earnings last month, spouse’s earnings last month, and any other household income received last month, including tips and bonuses. All questions were of pre-tax income. We collected this data monthly from October 2009 through April 2013.

Because income is a critical control variable, all our analyses will be conducted on ALP Financial Crisis Survey waves covering period October 2009 forward.

Results

In our regression analyses, the left-hand variable is defined as the inverse hyperbolic sine of spending in a month. This transformation, which we will use in all the regressions and so do not mention it each time, is approximately the same as log 2 plus the log of spending, except at zero and near-zero spending where it is approximately the same as spending. This transformation allows us to retain spending values of zero. The main right-hand variable is the previous month’s subjective probability of unemployment with a scaling from 0 to 100. Other right-hand variables are indicator variables for the month (to account for seasonality in spending), household size, and marital status. Most of the regressions also include the log of household income. The regression is over workers because of our interest in changes in household spending in response to changes in the unemployment expectations while still working, and not in spending changes in response to actual transitions from working to unemployed.

We will first show results in Tables 1, 2 and 3 that use a restricted time period, October, 2011 – April, 2013. We make this restriction because for this time period we asked a sub-sample of respondents about all spending items each month, including big-ticket items and automobiles. Thus we can relate *total* spending to subjective probabilities on a month-to-month basis. In earlier time periods, we only asked quarterly about big-ticket items and some infrequently purchased items. Merging the monthly and quarterly items into a framework where we are interested in the response to monthly changes in the subjective probability of unemployment is not straightforward, and so we do not do that here. In subsequent results (Table 4), we use data from October 2009 – April 2013. Over this period, we asked about a subset of total spending each month, and so the latter results will be based on a subset of spending.

Table 1 has the results of a descriptive cross-sectional OLS regression where the left-hand variable refers to total spending (transformed), including spending on nondurables, durables, and automobiles. Because the transformation of spending equals a constant plus (approximately) log spending, the interpretation of a coefficient on a right-hand variable is in terms of log percentage points. Thus, if the subjective probability of unemployment increases from 0 to 1.0, spending would decrease by 19%, according to these results. This is a substantial change, and it is highly statistically significant based on a standard error that accounts for multiple observations on the same individuals. As would be expected, Table 1 also shows that single-person households consume much less than married-person households, about 45% less. Spending increases with the number of household members, but not monotonically. The month indicators show seasonality, with expected spending in December 11% higher than spending in January.

An obvious missing variable from the regression reported in Table 1 is household income. Its inclusion is important because of a negative correlation between the subjective probability of unemployment and income. We include the logarithm of total monthly income as a right-hand variable in Table 2. Doing so shows that an increase in the subjective probability of unemployment from 0 to 1 reduces expected spending by 6 percent—a level much below the 19 percent seen in Table 1, and short of statistical significance.

Income has a coefficient of 0.29, which can also be interpreted as the elasticity of spending with respect to monthly income. If our income measure were permanent income, the elasticity should approach 1.0; but monthly income differs from permanent income because of transitory income and because of measurement error. When we control for income, the reduction in spending associated with single-person households is 22%, much less than in Table 1. When income is included in the model, spending increases monotonically as the number of family members increases. There is little change in the seasonal patterns.

Table 3 presents the results of fixed-effects regressions of the logarithm of spending on the subjective probability of unemployment and other control variables. Because the estimation is fixed effects, the variation in spending and in the right-hand variables comes from deviation from the household means. Thus it is natural to think of the variation in the subjective probability of unemployment as result of new information or shocks. While we include all the controls of Tables 1 and 2, we only show the coefficients on the subjective probability of unemployment and log income in Table 3.

Line 1 shows the results when the left-hand variable is total spending. It shows no effect of the subjective probability of unemployment on total spending; the model yields a coefficient of -0.002, which is both close to zero and of no statistical significance. The coefficient on log income is much smaller than in the cross-sectional model. In this fixed-effects model, this represents the estimated response to transitory income shocks.

Components of spending

In prior work, we found that some components of spending such as mortgage payments did not change following actual unemployment while others such as spending on clothing decreased quickly and substantially. Guided by our prior results on actual unemployment as well as by intuition, we selected a sub aggregate of total spending based on 21 items plus 8 big ticket spending categories that comprise 42% of total spending, and that might respond quickly to change in the probability of unemployment. Line 2 of Table 3 shows results based on cross-section estimation, not controlling for household income. In this model, a change in the subjective probability of unemployment from 0 to 1 would reduce total spending by 37%. When adding income to the model as in line 3, however, the coefficient is reduced to an insignificant -0.07. Of course, as we discussed earlier, the cross-sectional estimate is likely to have a downward bias because those with persistently high subjective probability of unemployment will likely have taken prior action, such as building up wealth. These actions allow them to consume at a higher level than those for whom the subjective probability of unemployment is the result of a short-term shock.

The fixed effects estimation in line 4 is, therefore, our preferred estimation method for finding the effects resulting from a shock to the unemployment expectation. As the subjective probability of unemployment increases from 0 to 1, it shows a highly significant reduction in household spending on the sub-set of categories of about 19 percent.

Expanded sample

We now present results based on the expanded monthly sample during October 2009 to April 2013. Of necessity, the components of spending that are aggregated to total spending are reduced to those for which we collected monthly data throughout the period. See the Appendix for the full list of 26 spending items. These categories cover about 60% of total spending.

We regressed the transformed spending of the sum of spending items asked every month for the entire sample on the subjective probability of unemployment, log income, and on the other controls given in Table 1. The first lines of Table 4 show the coefficients on the subjective probability of unemployment and on log income for the sum of the 26 items from OLS regressions and from estimating fixed effects models. Across all items, we did not find a significant reduction in spending in response to an increase in the subjective probability of unemployment. The OLS coefficient was -0.067, and the fixed-effects coefficient was -0.038. While both were negative, neither was statistically significant.

A possible reason for the lack of an effect is that the sum includes some categories where spending is quite rigid in the short run. Many categories of spending, such as mortgage payments, cannot be adjusted in the short term. Others, such as clothing, can. For this reason, in addition to total spending, we study changes in spending by category to determine if spending in some categories changes more than that in others in response to changes in expectations.

The remainder of Table 4 shows the results for those individual items where the p-value for the item was less than 0.10 in the fixed effect regression. We found four categories for which an increase in the subjective change in unemployment led to a statistically significant reduction in spending: drinking/dining out, personal care products and services, clothing and apparel, and entertainment/tickets to movies or events. For other transportation expenses, we estimated a statistically significant increase in spending.

We find that spending on drinking or dining out decreased significantly in both models (OLS and fixed effects), with such spending decreasing 10.6 percent in the fixed effects model for an increase in the subjective probability of unemployment from zero to 1. This result is in accord with our findings in previous work which used data on spending change following actual unemployment. In that work, we found that in the first two months of unemployment, spending on dining out decreased 49 percent, a much greater reduction than the 11 percent drop in total spending (Hurd and Rohwedder, 2013).

In Table 4, spending on personal care decreases 12 percent in the fixed-effects estimation for an increase in the subjective probability of unemployment from zero to 1. Spending on clothing had the largest percentage decrease of any category, which is in accord with the response to actual unemployment. In the fixed-effects estimation, monthly spending on clothing and apparel decreases nearly 14 percent for an increase in the subjective probability of unemployment from 0 to 1. In actual unemployment, such spending decreases 61 percent after two months. Spending on entertainment and tickets to movies and events also diminishes substantially as the expectation of unemployment increases.

The only category where spending increases significantly in the subjective probability of unemployment is "other" transportation expenses. This suggests a substitution toward cheaper public transportation in the face of likely unemployment.

Conclusions

Economic theory suggests that anticipations of a negative economic shock should lead households to reduce spending even prior to the shock so as to build up buffer-stock savings. The savings can be used to smooth consumption at least partially should the shock actually occur. However, for a number of shocks this anticipatory response should be rather modest. For example, suppose that unemployment leads to a loss of one year of earnings, which may be the result of actual unemployment and of a subsequently reduced wage on re-employment. Consider a 40 year-old man who will work until age 65. Unemployment will lead to a loss of 1/25th or 4% of rest-of-lifetime earnings. If that man has no savings but can borrow against future earnings, unemployment should lead to a decline in consumption of 4%. If while still employed, his subjective probability of unemployment increases from 10% to 30%, his expected lifetime earnings will have declined by 0.8%, and he should reduce consumption by that amount. Such a small reduction in response to a rather large increase in the subjective probability of unemployment is likely to be difficult to detect in data.

However, some households may be liquidity constrained, in which case a greater reduction would be warranted to avoid the risk of a 100% reduction in consumption that would come with actual unemployment. Furthermore, because some categories of spending such as spending for housing are difficult to adjust in the short to medium run, an individual should concentrate spending reductions in those categories that are flexible. Thus, it is important to estimate the effects of unemployment anticipations on sub-categories of spending as well as on total spending.

In fixed-effects estimations, we found no significant effect of the subjective probability of unemployment on total spending. Nevertheless, when using a subset of total spending with categories chosen for anticipated flexibility, we estimated a decrease in total spending of 19 percent for a change in subjective probability of unemployment from zero to 1.

When we focused on individual categories of spending, we estimated that an increase in the perceived probability of unemployment from zero to 1.0 led to an 11 percent reduction in expenditures for dining out, a 12 percent reduction for personal care expenditures, a 14 percent reduction in clothing expenditures, and an 11 percent reduction in entertainment expenditures. We found these results striking because several of them are exactly the same categories where, in prior research, we found that spending was reduced most strongly following actual unemployment. These results, along with the concordance with prior findings, have led us to conclude that unemployment expectations are a partial determinant of spending, and that further investigations of the magnitudes are warranted.

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Appendix 1

Items queried each month, grouped by actual screen display

Screen 1:

Mortgage: interest & principal
Rent
Electricity
Water
Heating fuel for the home
Telephone, cable, Internet
Car payments: interest and principal

Screen 2:

Food and beverages: food and drinks, including alcoholic, that you buy in grocery or other stores	
Dining and/or drinking out: items in restaurants, cafes, bars and diners, including take-out food	
Gasoline	
Other transportation expenses: parking, tolls, public transport, taxi and similar (please exclude spending on trips and vacations)	Category added in wave 21 (Nov10)

Screen 3:

Housekeeping supplies: cleaning and laundry products
Housekeeping, dry cleaning and laundry services: hiring costs for housekeeping or home cleaning, and amount spent at dry cleaners and laundries
Gardening and yard supplies: yard, lawn and garden products
Gardening and yard services: hiring costs including materials they provided

Screen 4:

Clothing and apparel: including footwear, outerwear, and products such as watches or jewelry
Personal care products and services: including hair care, shaving and skin products, amount spent at hair dresser, manicure, etc.
Prescription and nonprescription medications: out-of-pocket cost, not including what's covered by insurance
Health care services: out-of-pocket cost of hospital care, doctor services, lab tests, eye, dental, and nursing home care
Medical supplies: out-of-pocket cost, not including what's covered by insurance

Screen 5:

Entertainment: tickets to movies, sporting events, performing arts, etc
Sports: including gym, exercise equipment such as bicycles, skis, boats, etc.
Hobbies and leisure equipment: such as photography, stamps, reading materials, camping, etc.

Screen 6:

Personal services: including cost of care for elderly and/or children, after-school activities
Education: including tuition, room and board, books and supplies
Other child or pet-related spending, not yet reported: including toys, gear, equipment and veterinarian

Items queried every three months, grouped by actual screen display

Respondents are asked to record the amount spent over the previous three calendar months in each category. The categories include seven big ticket items and 11 other less frequent spending categories.

Screen 1:

Big ticket items

- Automobile or truck
- Refrigerator
- Stove and/or oven
- Washing machine and/or dryer
- Dishwasher
- Television
- Computer

Follow-up questions on big ticket items queried amounts, and in the case of cars how the purchase was financed.

Screen 2:

Homeowner's or renter's insurance
Property taxes
Vehicle insurance
Vehicle maintenance: parts, repairs, etc.
Health insurance

Screen 3:

Trips and vacations
Home repair and maintenance materials
Home repair and maintenance services
Household furnishings and equipment: such as furniture, floor coverings, small appliances, miscellaneous household equipment
Contributions to religious, educational, charitable, or political organizations
Cash or gifts to family and friends outside the household

Table 1

Regression of log total monthly spending on the subjective probability of unemployment and controls. Cross-section.				
	Coefficient	Standard error	t-statistic	p-value
Probability of unemployment (0 - 1)	-0.191	0.058	-3.3	0.001
Single	-0.446	0.035	-12.6	0.000
Other HH members				
1	0.029	0.042	0.7	0.495
2	0.097	0.043	2.3	0.023
3+	0.037	0.048	0.8	0.441
month 1				
2	-0.022	0.016	-1.4	0.158
3	0.018	0.017	1.1	0.292
4	0.042	0.025	1.7	0.099
5	0.045	0.027	1.7	0.098
6	0.126	0.027	4.7	0.000
7	0.081	0.027	3.0	0.003
8	0.082	0.027	3.1	0.002
9	0.074	0.025	3.0	0.003
10	0.025	0.021	1.2	0.215
11	0.014	0.017	0.8	0.424
12	0.109	0.017	6.4	0.000
Constant	8.136	0.037	219.6	0.000

Notes: month 1 refers to spending in January and similarly for the other months.
N = 11,651. Standard errors adjusted for multiple observations on same households.
R-squared = 0.111

Table 2

Regression of log total monthly spending on the subjective probability of unemployment, income, and controls. Cross-section.				
	Coefficient	Standard error	t-statistic	p-value
Probability of unemployment (0 - 1)	-0.060	0.049	-1.2	0.220
Log income	0.287	0.033	8.7	0.000
Single	-0.221	0.041	-5.4	0.000
Other HH members				
1	0.039	0.032	1.2	0.226
2	0.118	0.034	3.5	0.001
3+	0.127	0.041	3.1	0.002
month 1				
2	-0.038	0.016	-2.4	0.016
3	0.012	0.017	0.7	0.471
4	0.023	0.024	1.0	0.340
5	0.017	0.026	0.7	0.511
6	0.098	0.028	3.5	0.000
7	0.060	0.027	2.2	0.026
8	0.052	0.026	2.0	0.043
9	0.032	0.024	1.3	0.184
10	0.011	0.020	0.6	0.563
11	0.018	0.017	1.0	0.297
12	0.105	0.017	6.1	0.000
Constant	5.644	0.300	18.8	0.000

Notes: month 1 refers to spending in January and similarly for the other months.
N = 11,650. Standard errors adjusted for multiple observations on same households.
R-squared = 0.305

Table 3

Selected estimated coefficients from regression of log spending on subjective probability of unemployment and controls.				
	Coefficient	Standard error	t-statistic	p-value
1. Total spending, fixed effects				
Probability of unemployment (0 - 1)	-0.002	0.028	-0.1	0.953
Log income	0.033	0.006	5.6	0.000
2. Sub-set of spending, OLS				
Probability of unemployment (0 - 1)	-0.366	0.125	-2.9	0.003
3. Sub-set of spending, OLS				
Probability of unemployment (0 - 1)	-0.073	0.109	-0.7	0.502
Log income	0.542	0.050	10.8	0.000
4. Sub-set of spending, fixed effects				
Probability of unemployment (0 - 1)	-0.186	0.079	-2.4	0.019
Log income	0.234	0.015	15.7	0.000

Notes: N varies between 11,650 and 12,242.
Standard errors adjusted for multiple observations on same households.
All regressions included indicators marital status, number of other household members, and month.
Sub-set of spending includes 20 items which comprise 42% of total spending.

Table 4. Selected coefficients from regression of categories of spending in logs

		OLS		Fixed effects	
		Coefficient	P-value	Coefficient	P-value
Sum of 26 items	P(unemployment)	-0.067	0.198	-0.038	0.198
	Log income	0.340	0.000	0.170	0.000
Drinking/dining out	P(unemployment)	-0.715	0.000	-0.106	0.011
	Log income	0.550	0.000	0.107	0.000
Personal care products and services	P(unemployment)	-0.388	0.001	-0.122	0.015
	Log income	0.410	0.000	0.090	0.000
Clothing and apparel	P(unemployment)	-0.544	0.000	-0.136	0.050
	Log income	0.517	0.000	0.099	0.000
Other transportation expenses	P(unemployment)	0.012	0.912	0.087	0.056
	Log income	0.205	0.000	0.081	0.000
Entertainment/tickets to movies, events	P(unemployment)	-0.658	0.000	-0.109	0.077
	Log income	0.379	0.000	0.033	0.009

Notes: N varies between 41,022 and 41,178 person-wave observations.
Standard errors in OLS estimations are adjusted for multiple observations on same households.
All regressions included indicators marital status, number of other household members, and month.
Sum of 26 spending items queried monthly comprises about 60% of total spending. See Appendix for complete list.