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Impact of Occupational Unemployment Risk on Household Spending

Christopher D. Cotton, Vaishali Garga, and Justin Rohan

Abstract:
The life-cycle consumption and permanent income hypotheses predict that if workers face greater likelihood of unemployment in the future that lowers expected future income, they will save more today. In this paper, we test this hypothesis by looking at the expenditure response of workers to the change in unemployment risk measured at the occupational level. We find that occupational unemployment risk does not have a large impact on consumption expenditure. However, despite investigating multiple forms of occupational unemployment risk for multiple expenditure categories in two expenditure surveys (PSID, CEX), we do not obtain narrow confidence intervals for our estimates, so there remains a possibility of a limited impact.

JEL Classifications: E21, E24, J64
Keywords: unemployment risk, expenditure, life-cycle consumption, permanent income

Christopher D. Cotton is an economist in the Federal Reserve Bank of Boston Research Department. His email address is Christopher.Cotton@bos.frb.org. Vaishali Garga is an economist in the Boston Fed's Research Department. Her email address is Vaishali.Garga@bos.frb.org. Justin Rohan is a research assistant in the Boston Fed's Research Department. His email address is Justin.Rohan@bos.frb.org.

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1 Introduction

The COVID-19 pandemic brought with it enormous dispersion in the degree of unemployment across occupations. Some occupations, especially those in the leisure and retail industries, experienced very high levels of unemployment. A key question was how this enormous disruption to employment would affect the economy more broadly, including consumption spending. An important component of this response is how workers employed in occupations that experienced unemployment, but who themselves remained employed, responded to higher levels of unemployment in their occupations.

Based on the life-cycle consumption and permanent income hypotheses, individuals prefer to smooth consumption over their lives based on their expected lifetime earnings. Therefore, we expect that in response to a greater risk of unemployment that lowers expected future income, workers would cut spending today to save for a rainy tomorrow. A number of papers in the literature have employed a variety of approaches to test these hypotheses. The novelty of each paper lies in its measure of unemployment risk, which is central to analyzing a workers' response to a change in expected future income. Some papers assume perfect foresight and proxy for unemployment risk using realized unemployment; others gauge unemployment risk using survey questions on the subjective probability of future job loss; still others measure unemployment risk as an estimated probability of job loss based on worker characteristics.

In this paper, we employ another novel measure of unemployment risk, which is at the level of the worker's occupation. The underlying idea is that if a high percentage of workers in an occupation become unemployed, other workers in that occupation who are currently employed may perceive a greater risk of future unemployment. Therefore, the unemployment statistics of an occupation may be useful indicators of its unemployment risk.

We focus on the largely unexplored effect of a change in occupational unemployment risk on the change in personal expenditure. We construct time-varying measures of occupational unemployment risk using employment data from the Bureau of Labor Statistics' (BLS) monthly Current Population Survey (CPS) and its Annual Social and Economic Supplement (CPS ASEC). We then examine the impact of changes in occupational unemployment risk on expenditure growth, using the Panel Study of Income Dynamics (PSID) and the Consumer Expenditure Survey (CEX). The panel structure of these surveys allows us to conduct the analysis at the household level, while controlling for income growth and conditioning on the worker remaining employed (so that we are capturing the impact of expected rather than realized income changes). We employ two different expenditure surveys because while the PSID allows us to analyze the relationship between unemployment risk and spending over a longer horizon (one or two years) across a wide range of occupations, the CEX allows us to investigate the relationship over a shorter horizon (nine months) for a wide range of disaggregated spending categories.

We investigate the impact of changes in four different measures of occupational unemployment risk on expenditure growth. First, we measure changes in occupational unemployment risk using the changes in the unemployment rate of an occupation. If the unemployment rate of an occupation changes significantly over a given time horizon, it is likely that workers who continue to be employed in that occupation perceive a greater risk of future unemployment. However, some occupations may be more prone to volatility in their unemployment rates because, for example, some occupations face greater demand swings across the business cycle. To control for the baseline differences in unemployment rate fluctuations between occupations, our second measure of change in occupational unemployment risk is the normalized change in the unemployment rate of an occupation. Using this measure, we can uniformly compare the impact of one standard deviation higher occupational unemployment risk on spending growth. Third, it is possible that workers' perception of their unemployment risk depends on the general duration of unemployment in their occupations. As the duration of unemployment increases, the prospect of unemployment carries with it a greater loss of income. To capture this, we measure changes in occupational unemployment risk using changes in the average duration of unemployment of an occupation. As before, we normalize the change in the average duration to eliminate baseline differences in the average duration between occupations. Lastly, it is possible that workers pay attention to both the level and the average duration of unemployment in their occupations when gauging their own future likelihood of unemployment. Therefore, our fourth measure of occupational unemployment risk is the sum of normalized change in occupational unemployment rate and the normalized change in the average duration of unemployment. Importantly, all four of our measures of changes in occupational unemployment risk are based on time-varying unemployment statics at the occupation level.

We do not find that occupational unemployment risk has a significant impact on expenditure growth. This result holds across all four of our measures of change in unemployment risk in both the PSID and CEX and across various disaggregated spending categories. However, the confidence intervals for our estimates across these different specifications are typically quite wide. Therefore, we are only effectively able to reject the presence of a large impact of occupational unemployment risk on consumption/savings.

We then pay special attention to the Great Recession period to see if we find any significant impact of occupational unemployment risk during this time period. It is possible that individuals are largely unaware of what is going on in their own occupations or choose not to react to occupational risk except during widespread recessions when this information is more widely available and realized unemployment carries greater risk (in terms of fewer opportunities for re-employment and greater persistence of unemployment). As such, individuals may only respond to significant shocks in occupational unemployment risk and ignore much of the normal year-to-year variation. However, we find that even during the Great Recession period, there is no significant impact of greater unemployment risk on expenditure growth. This is true in both the expenditure surveys across all four risk measures and across several different spending categories.

Theory suggests that if a rise in occupational unemployment risk raises workers' perceived risk/likelihood of unemployment, they should cut their consumption. We have not been able to find evidence of this relationship in our data. A potential reason why such a relationship may not exist is that occupational unemployment risk does not translate one-for-one into workers' perceived unemployment risk. It is possible that workers, when estimating their unemployment risk, pay little attention to the employment status of other workers in similar jobs, and perhaps instead focus on either aggregate unemployment or more granular individual performance statistics. Of course, one alternative is that the relationship does exist but is too small to be picked up by our relatively wide confidence intervals.

Related Literature

Our paper relates to four main bodies of literature. First, we contribute to the handful of existing papers studying how occupation-based unemployment risk impacts consumption. Our work is most similar to Juelsrud and Wold (2019) who study the impact of the international oil price collapse on savings across occupations that were differentially impacted by the collapse. Specifically, they compare engineers, an occupation more likely to be impacted by the oil price collapse, to other similarly high-skilled workers in occupations less likely to be impacted, and find that a 1% increase in job-loss risk leads to a 1.2–2% increase in liquid savings. This is the only other paper we are aware of that looks at how changes in occupational unemployment risk over time dynamically change consumption and saving decisions. Skinner (1988) uses a static approach and measures differences in savings rates across the cross section of occupations in the 1972–1973 Consumer Expenditure Survey. Somewhat counterintuitively, he finds that the overall savings rates are lower among occupations that are generally associated with greater income risk. Shore and Sinai (2005) find that couples in the same occupation, who therefore have strongly correlated unemployment risks, spend relatively more on non-rental housing. Our paper is different from the others in this literature as our approach enables us to use several decades of data—we observe many shocks to unemployment risk over a long period of time—to analyze the impact of changes in unemployment risk on consumption spending.

Closely related to our own paper is the broader literature documenting the sorting of workers into occupations based on their risk preferences. As explained by Skinner (1988), if individuals self-select into their occupations based on their unemployment risk tolerance, then we may not observe changes in consumption in response to changes in unemployment risk. Studying this question of self-selection, Fuchs-Schündeln and Schündeln (2005) do find evidence that individuals select into careers based on risk tolerance by observing civil servants in East and West Germany during the Reunification period. Using a sample of Dutch graduates (at various levels of education), Fouarge, Kriechel and Dohmen (2014) also find evidence of students sorting and switching into occupations such that their economic preferences mirror the risk profile of their occupations. We look at how dynamic changes in occupational unemployment risk affect spending and saving in order to overcome the bias that certain individuals in certain occupations may be prone to generally save more.

A third body of literature closely related to our own is the one analyzing the impact of more general (not occupational) unemployment realization and unemployment risk changes on consumption growth. Most papers looking at the impact of unemployment and unemployment risk on spending focus on food spending (Harmenberg and Ôberg 2019; Dunn 1998; Benito 2006) because food spending, unlike much of consumer spending, is not fixed and can be easily changed when individuals become unemployed (Chetty and Szeidl 2007; Kingston 1978; Burgess 1981). Using this approach, Stephens (2004) finds that individuals cut food spending considerably when they become unemployed. Gruber (1997) shows that larger unemployment benefits lead to smaller reductions in food spending. Hendren (2017) examines whether individuals alter their food spending in the years prior to job loss. He finds using data from the Panel Study of Income Dynamics (PSID) that individuals cut food spending by 2.7% in the years prior to becoming unemployed. Interestingly Stephens (2004) shows that a household's ability to anticipate future unemployment does not lower the reduction in food spending once they become unemployed. This finding disagrees with Karahan, Moore and Pilossoph (2019), who find that declines in spending are much larger for households that do not anticipate future unemployment.[1] Our paper is similar to other papers in this literature in that we look specifically at what impact unemployment risk has on food spending. However, unlike these other papers, our measures of unemployment risk are at the occupational level. Specifically, we look at how other people in the same occupation becoming unemployed affects a worker's spending when that worker remains in the same occupation.

Lastly, we contribute to an even broader literature analyzing whether households undertake precautionary savings in response to changes in uncertainty in future income or unemployment. In this literature, many authors measure uncertainty in future income based on unemployment risk. One approach is to compare survey questions asking respondents about their probability of becoming unemployed with their expected consumption changes (Guiso, Jappelli and Terlizzese 1992; Lusardi 1998; Guariglia 2001). Other papers rely on more indirect approaches based on geography. Mody, Ohnsorge and Sandri (2012) look at, among other variables, national unemployment rates to compare precautionary savings across countries during the Great Recession. Engen and Gruber (2001) look at how variation in state-level unemployment insurance programs impact precautionary saving behavior. Also taking a geography-based approach, Carroll, Dynan and Krane (2003) use region as an instrumental variable for unemployment risk. Other more unique measures of uncertainty have also been used in the literature. For instance, Di Maggio et al. (2020) use a novel employer-employee matched dataset to use an individual's employer as a measure of income variability. We try to use occupation as a measure of unemployment risk when measuring precautionary savings behavior, although our approach does not allow us to disentangle the changes in the expectation of future income from changes in the variance of future income.

The remainder of this paper is structured as follows. Section 2 discusses the expenditure and employment data used in the analysis. Section 3 describes the empirical framework and the four different measures of occupational unemployment risk. Section 4 discusses the results on the impact of changes in unemployment risk on expenditure growth. Section 5 concludes.

2 Data

To examine the role of occupational unemployment risk in driving consumption we use two complementary longitudinal household-level survey datasets—the Panel Study of Income Dynamics (PSID) and the Consumption Expenditure Survey (CEX). The PSID allows us to study many different occupations and investigate the question back to the 1970s, while the CEX allows us to conduct our analysis at a higher frequency and for more granular spending categories. We pair these surveys with occupational unemployment data gathered from either the monthly Current Population Survey (CPS) or its Annual Social and Economic Supplement (ASEC) depending on whether monthly or annual data is needed.

[1] Stephens (2004) analyzes food spending from the first four waves of the Health and Retirement Study, while Karahan, Moore and Pilossoph (2019) analyzes total spending and spending categories such as vacations, cars, durables, and housing, from the Survey of Consumer Expectations.

PSID The PSID began as an annual survey asking a sample of ~4,800 families questions about their employment, income, expenditure, and a variety of other topics. Each household was assigned a "reference person" whom the PSID continued to interview about their family in the following years. The children of these families then became reference people of new PSID households once they left home. In this way the PSID has continued interviewing the original sample and their descendants from 1968 to the present.[2] While the survey was originally conducted annually, since 1997 the survey has been conducted once every two years. The most recent wave in our dataset was conducted in 2017, at which time the core sample contained 9,607 families. Using the publicly available family and individual level data, we create a dataset containing responses from 43 waves of surveys.[3]

The PSID asks respondents how much they have spent in different expenditure categories over the last year. At the start of the survey, there were only a few questions about expenditure, mainly focusing on food spending. However, since 1999, the survey has expanded to ask additional spending questions to paint a more complete picture of the PSID respondents' spending behaviors. Therefore, while focusing on food spending gives us extended coverage (in terms of sample size), we are also able to use the data from the more recent waves to assess how occupational unemployment risk affects other categories of spending as well.

The PSID also records the occupation of the reference person. In each survey, respondents are asked to describe what they do for work. These responses are then translated to a specific Census Occupation Code by a team of "occupation coders." This translation step allows the PSID to use very granular occupation categories but also introduces the potential for miscoding of occupations. We control for some of the possibility of misclassification by using information on the respondent's *job* as well as occupation. For example, when requiring respondents to be continuously employed in the same occupation between the two surveys, we require them to have the same occupation code as well as same job in the two surveys.

CEX The CEX collects information on spending via two types of surveys—an Interview Survey and a Diary Survey. We use data from the Interview Surveys as they capture most major/recurring purchases. Specifically, we join the individual and family level data available in the CEX Public Use Microdata (PUMD) files available from 1996–2018. The CEX is a monthly survey in which each respondent is interviewed four times over the course of a year (which may not necessarily be a calendar year) about their spending over the previous three months. As this survey is frequent and only asks about spending over a short period, respondents are more likely to be able to recall their spending accurately. Additionally, because of the short three-month recall window, the CEX respondents can be expected to more accurately report their spending in a large number of granular spending categories.

Historically, CEX respondents were asked about their employment (occupation and income) only in the first and fourth interviews. Specifically, respondents were asked whether they had worked any number of weeks in the past 12 months. If the answer to this question was yes, then they were asked what their income and occupation over this period was. Unlike the PSID, CEX

[2] The survey also added immigrant refresher samples in 1990, 1997, and 2017.

[3] We thank Daniel Cooper for his help with gathering and formatting the PSID and CEX data.

respondents directly assign themselves one of fifteen occupation groups.[4] The lower granularity of the occupation groups implies that there is less potential for occupational coding issues than in the PSID but also implies potentially lower variation in our occupational unemployment risk measures.

CPS We construct our measures of occupational unemployment risk using the monthly Current Population Survey (CPS) and its Annual Social and Economic Supplement (CPS ASEC).[5] The monthly survey contains a rotating sample of ~60,000 households, whereas the CPS ASEC is a yearly survey of ~98,000 families. Both surveys record the respondent's occupation and current employment status.

To ensure consistent variable definitions over time, we use harmonized CPS and CPS ASEC datasets available from IPUMS CPS.[6] Harmonized monthly CPS survey data is available going back to 1976, while annual data is available going back to 1962.

The PSID began in 1968 and is measured annually or biannually so we combine it with the CPS ASEC, which covers the full PSID sample. Both the PSID and the CPS ASEC use Census Occupation Codes to classify occupations. However, these codes are periodically updated to reflect changes in the underlying occupations, and the PSID has not always been as timely as the CPS ASEC in implementing the occupation codes revision.[7] When the codes between the PSID and CPS ASEC do not align, we cannot directly assign the occupational unemployment risk calculated using the CPS ASEC to occupations in the PSID. To get around this issue, we use harmonized occupation codes provided by IPUMS CPS. These harmonized codes provide a static set of occupations to which each set of unharmonized occupation codes (both in the CPS ASEC and PSID) can be mapped. Three versions of these codes are available—OCC1950, OCC1990, and OCC2010—each named after the set of unharmonized codes that they are based on. While each set of harmonized codes can be mapped to every set of unharmonized codes, large changes to the underlying unharmonized codes can still cause sudden jumps in the number of workers categorized into each harmonized occupation. To minimize these spurious jumps (due to code recategorization), prior to 2003, we map the occupation codes to OCC1990 codes and after 2003, we map all occupation codes to OCC2010 codes. This allows us to ensure that for each year, the

[4]Originally, the CEX had 18 occupation groups instead of 15; however, in 2013 "Machine Operator, Assembler, Inspector," "Transportation Operator," and "Handler, Helper, Laborer" were combined into "Machine or Transportation Operator, Laborer." To have a static set of occupation codes over our panel, we consider only this combined group.

[5] One alternative would be to measure the occupational unemployment risk of the occupations within our longitudinal datasets. However, this is hard to do in both the PSID and the CEX. In the PSID, there are many occupations, so there are relatively few workers in each occupation, rendering any occupational unemployment statistics imprecise. In the CEX, there is no direct indicator of the respondent's current employment status.

[6]IPUMS CPS is a publicly available integrated set of CPS microdata available from 1962 to the present, created by the Minnesota Population Center in collaboration with Unicon Research Corporation.

[7] The PSID recorded all occupations from 1968 through 2003 using the 1970 Census Occupation Classification Scheme. (These codes were not originally used for occupations recorded prior to 1981; however, a retrospective coding process later assigned all occupations from 1968 through 1980 to the same 1970 Census Occupation codes.) In 2003 the PSID began recording occupations using the 2000 Census Occupation Classification Scheme. These were again replaced in 2017 by the 2010 Census Occupation Classification Scheme. At the start of the PSID in 1968, the CPS used 1960 Census Occupation Codes. The CPS then updated occupation codes in the years following each decennial census (for exact years see Appendix C.1).

set of harmonized codes that we use roughly resembles the unharmonized codes being used by the surveys.

The CEX began in 1996 and conducts surveys every month so we combine it with the monthly CPS. Since the 15 occupation codes used in the CEX are not directly compatible with the occupations codes in the CPS, we first create a crosswalk from one set of codes to the other. To account for the coding scheme in the CPS changing over time, we create this crosswalk between the CEX occupation codes and the harmonized OCC2010 codes available from IPUMS CPS. This process involves manually matching each of the harmonized OCC2010 codes with one of the 15 CEX occupation codes. Using this crosswalk, we then calculate our various measures of occupational unemployment risk for each CEX occupation from 1996 through 2018 based on the employment information in the monthly CPS surveys.

3 Empirical Framework

In this section, we explain our empirical approach. Our basic regression model, given in equation (1), regresses the change in an individual's occupational unemployment risk on the change in their spending between surveys. i represents an individual while t represents time.[8] We use logs so that the changes of high consumption individuals do not dominate. Our primary variable of interest is the change in occupational unemployment risk, the impact of which is captured by the coefficient α. A rise of 0.01 unit in unemployment risk implies an α percentage point rise in the growth rate of expenditure.[9] We simultaneously control for the individual's income growth between the surveys to capture the fact that spending may also be driven by income changes that are likely to be correlated with changes in unemployment risk. The response of expenditure growth to income growth is captured by the coefficient β. A one percentage point rise in income growth implies a β percentage point change in the expenditure growth.[10] Dummy variables (γ_t) control for the common trends across all individuals over time.

$$(\Delta \ln(expenditure))_{i,t} = \alpha(\Delta unemployment\_risk)_{j,t} + \beta(\Delta \ln(income))_{i,t} + \gamma_t + u_{i,t} \qquad (1)$$

In order to the isolate the impact of changes in unemployment risk on consumption growth, we only consider those individuals who remain employed in the same occupation between surveys; otherwise, changes in spending could result from a change in employment status or a change in

[8] Note that in the PSID t represents one year while in the CEX t represents one month. Therefore, in the PSID, for years after 1997 (when the survey is conducted biannually) equation (1) should be written as:

$$(\Delta_2 \ln(expenditure))_{i,t} = \alpha(\Delta_2 unemployment\_risk)_{j,t} + \beta(\Delta_2 \ln(income))_{i,t} + \gamma_t + u_{i,t}$$

As CEX survey participants are only asked about the occupation in the first and last survey, the change in consumption in the CEX data is actually measured across nine months, even though the survey is conducted every 3 months. Therefore, when using data from the CEX equation (1) should be written as:

$$(\Delta_9 \ln(expenditure))_{i,t} = \alpha(\Delta_9 unemployment\_risk)_{j,t} + \beta(\Delta_9 \ln(income))_{i,t} + \gamma_t + u_{i,t}$$

[9] We use the terms expenditure and consumption interchangeably. Also both unemployment rate and spending growth are measured from 0 to 1 rather than 0 to 100.

[10] Note that we consider the change in $\ln(expenditure + 1)$ as well as $\log(income + 1)$ to keep instances where an individual reports an expenditure/income value of 0 from being excluded from the sample.

occupation. We also remove outliers based on income and consumption changes—following Zeldes (1989) and Gruber (1997), we remove individuals who report an absolute value of the change in log income/consumption greater than 1.1, which restricts the rise or fall in these variables to be approximately 300%. To remove the impact of inflation over time, we deflate the income and consumption data using the PCE Deflator for the PSID and the quarterly CPI for the CEX. Lastly, we cluster the standard errors in order to account for the common variation coming from individuals being in the same occupation at the same time. In the PSID, standard errors are clustered by occupation × year, whereas in the CEX they are clustered by occupation × month-year, which is the level variation of our main variable of interest (change in the occupational unemployment risk).

We compute the change in unemployment risk at the occupation level and in four different ways. First, we look at the change in the unemployment rate of an occupation between the two relevant surveys. This is shown in equation (2).

$$(\Delta unemployment\_risk)_{j,t} = \Delta u_{j,t} = unemployment\_rate_{j,t} - unemployment\_rate_{j,t-1} \tag{2}$$

$\Delta u_{j,t}$ is the change in the unemployment rate of occupation j between survey t and $t-1$.[11] The idea here is that workers may infer their unemployment risk based on the realized change in the unemployment rate of their occupations.

Second, we consider the normalized change in the occupational unemployment rate. This is shown in equation (3).

$$(\Delta unemployment\_risk)_{j,t} = \frac{\Delta u_{j,t} - \overline{\Delta u_{j,p}}}{\sigma_{\Delta u_{j,p}}} \tag{3}$$

To normalize, we subtract the mean change in unemployment and divide by the standard deviation of the change in unemployment for occupation j. We do not compute the mean and standard deviation over all years because the definitions of occupations change over time. Instead, p represents the range of survey years where the CPS used the same Census Occupational Coding Scheme (to see exact ranges used see Appendix C). $\overline{\Delta u_{j,p}}$ is the average value of $\Delta u_{j,t}$ over the set of years p where $t \in p$. $\sigma_{\Delta u_{j,p}}$ is the standard deviation of $\Delta u_{j,t}$ over the set of dates p. This normalization accounts for the differences in the baseline volatility of unemployment rates across occupations. We do this because workers in all occupations may not infer the same level of unemployment risk based on the realized change in the unemployment rate of their occupations. A worker whose occupation has a lower baseline volatility in the unemployment rate may react more to a given rise in the unemployment rate than a worker whose occupation has a higher baseline volatility in the unemployment rate.

Third, we measure occupational unemployment risk based on the normalized change in the average duration of unemployment of an occupation—that is, based on how long workers in an occupation typically remain unemployed.

$$dur_{j,t} = \frac{1}{n}\sum_{i=1}^{n} max(dur_i) \tag{4}$$

[11] This is technically computed between survey t and $t-2$ (t being years) when the PSID is conducted biannually, and it is computed between survey t and $t-9$ (t being months) for the CEX.

$$\Delta dur_{j,t} = dur_{j,t} - dur_{j,t-1} \tag{5}$$

$$(\Delta unemployment\_risk)_{j,t} = \frac{\Delta dur_{j,t} - \overline{\Delta dur_{j,p}}}{\sigma_{\Delta dur_{j,p}}} \tag{6}$$

To calculate the duration of unemployment, we use a question from the CPS asking those respondents who are unemployed how long they have been unemployed.[12] This question is only asked to those members of an occupation who are unemployed, so there is a limited number of responses every month. Therefore, to get more precise estimates of this measure, we calculate duration using an average of all monthly CPS data over the preceding 12 months for the PSID, and the preceding nine months for the CEX.[13] One issue that arises from using multiple monthly surveys to calculate average duration is that because of the CPS' rotating panel design, the same individuals appear in multiple CPS surveys. To bypass this issue, we look at the maximum duration of unemployment reported by each individual over the relevant period so that we count each unemployed worker only once. Additionally, to make sure that our estimates are precise, we require that every occupation have a minimum total number of unemployed workers (at least 20) across the entire relevant period.[14] This duration measure is given in equation (4). n represents the number of unemployed individuals in occupation j during the relevant period as of survey s. The variable $max(dur_i)$ represents the maximum duration of unemployment reported by individual i during the relevant period as of time t. Therefore, to calculate the average duration of unemployment for occupation j at time t, we take the mean of the n workers' maximum duration of unemployment. In equation (5), we then calculate the change in average duration of unemployment using the same method as equation (2). Lastly, in equation (6), we normalize the change in this duration measure (to account for baseline differences in average duration of unemployment across occupations).

Our final measure of unemployment risk is a combination of our second and third measures. It is based on the idea that individuals infer unemployment risk based on a combination of the normalized change in the unemployment rate of their occupations and the normalized change in the typical duration of unemployment in their occupations.

$$combined_{j,t} = \frac{\Delta u_{j,t} - \overline{\Delta u_{j,p}}}{\sigma_{\Delta u_{j,p}}} + \frac{dur_{j,t} - \overline{dur_{j,p}}}{\sigma_{dur_{j,p}}} \tag{7}$$

$$(\Delta unemployment\_risk)_{j,t} = \frac{combined_{j,t} - \overline{combined_{j,p}}}{\sigma_{combined_{j,p}}} \tag{8}$$

To capture this we add the normalized change in the unemployment rate with the normal-

[12]Unlike our other measures of unemployment risk, when using consumption data from the PSID, we calculate the duration of unemployment using data from the monthly CPS survey, not the yearly CPS ASEC survey. Doing so limits the number of years of data we are able to analyze in the PSID. However, the additional observations available in the monthly survey are required in order to have a sufficient sample size to calculate the average duration of unemployment by occupation.

[13]In the PSID, this 12-month period reflects the minimum amount of time between surveys. In the CEX this nine-month period reflects the number of months between an individual's first and fourth surveys. Using these average windows allows us to use the maximum amount of data when computing the change in the average duration between surveys.

[14]When calculating the change in duration between surveys, we therefore require an occupation to have at least 20 unemployed individuals over the relevant period at the time of the current survey and the previous survey.

ized average duration of unemployment. This is given in equation (7), using the same variable definitions as in the previous equations. We then re-normalize this combined measure using the same method as in equation (3) and equation (6) so that a change of 1 in the unemployment risk measure represents a change of 1 standard deviation in the combined measure. This normalized combined unemployment risk measure is given in equation (8).

For both the CEX and PSID, three additional restrictions are added to the data to ensure the accuracy of our results. We first discuss the PSID restrictions and then discuss the corresponding restrictions for the CEX.

In the PSID, first we restrict the years to those in which there are no changes in the occupation coding scheme. As discussed in Section 2, we use a crosswalk to convert PSID occupation codes to harmonized CPS occupation codes. In the years where the crosswalks change (because either the CPS or the PSID updates its unharmonized occupation coding scheme), the occupation codes assigned to workers could change—even when there was no change in their actual occupation—simply due to a coding scheme change. This can cause jumps in unemployment statistic, which are unrelated to any meaningful changes in the labor market. We mitigate this issue to some degree by using two sets of harmonized occupation codes, which means that the differences between the unharmonized and harmonized codes are not as large. To further avoid this issue, we drop "switch years" where either the CPS ASEC or PSID switches the Census Occupation Coding Scheme being used.[15]

Second, we restrict the sample to individuals who report being employed in the same job in the period over which expenditure growth is measured. An individual who has not switched jobs could nevertheless be coded as being in a different occupation from one survey to the next. To prevent this issue, we look at the number of months individuals say they have been working in the same job instead of just comparing the occupation codes assigned to a respondent. For respondents who report working in their current job for longer than the amount of time elapsed since their last PSID survey, we assume that they are working in the same job as their last survey (and therefore, the same occupation). We also limit to respondents working only one job and not self-employed in order to ensure the accuracy of this same-job measure.

Third, we restrict the minimum number of respondents required in an occupation to be able to accurately compute its unemployment rate. We compute the unemployment rate for the PSID occupations from the CPS ASEC. There are a lot of occupations in the PSID. Therefore, while the CPS ASEC has a considerable overall sample size, the sample size within particular occupations is sometimes limited, making it difficult to get an accurate measure of unemployment risk. To address this issue, we require that an occupation have at least 100 respondents in the two relevant survey periods when computing the change in unemployment risk for an occupation; otherwise all members of that occupation are excluded from the sample.

We make a number of similar modifications to work with the CEX. First, unlike the PSID, there is no direct question asking respondents about their employment status (whether they are employed or unemployed), which means that we cannot condition on an individual remaining employed between surveys. To get around this issue, we use the income data reported in the CEX. If an individual is unemployed for a period of time, they should then report a decrease

[15]To see exactly which years these are see Appendix C.

in income over that period, so we hope that simultaneously controlling for income growth in our regression indirectly controls for any change in the employment status. Second, it is also important to account for the unique interview timing structure of the CEX. Each time someone is interviewed for the survey, they provide information on their spending in the prior three months. We adjust these figures for inflation by dividing by the average CPI over this three-month period. Note that our dependent variable is the difference between the reported spending in the current period (for the prior three months) relative to the report spending from three quarters ago (for the preceding three months as of three quarters ago). To ensure that the timing of spending growth, occupational unemployment risk change, and income growth line up, we compute the change in unemployment risk and income growth over the same period as spending growth. Third, when calculating $\Delta u_{j,t}$ using the CEX, it is important to consider that we are looking at the change in monthly unemployment rates. As there is likely significant seasonality in the unemployment rate of some occupations, we cannot just take the difference between the unemployment rate during the fourth survey at time t and the first survey at time $t-9$. Instead we look at the difference in the year-over-year change in the occupational unemployment rate. This is shown in equation (9).[16]

$$\Delta u_{j,t} = (u_{j,t} - u_{j,t-12}) - (u_{j,t-9} - u_{j,t-21}) \tag{9}$$

4 Results

We now look at the results of our regressions studying the impact of occupational unemployment risk on consumption spending in the PSID as well as the CEX. To start we evaluate the impact of unemployment risk on grocery spending. We focus first on grocery spending because it is widely used in the literature when attempting to detect consumption-smoothing behavior (Stephens 2004; Gruber 1997; Hendren 2017). It is also the broadest expenditure measure for which spending is assessed in the PSID for each year of the survey. Table 1 presents the results. The four columns of the table correspond to four different regressions, each using a different measure of occupational unemployment risk. We find a positive significant association between annual income growth and spending growth across all four specifications. A one percentage point higher annual income growth leads to a 0.0433 percentage point higher growth in grocery spending.

Turning to our variable of interest, the change in occupational unemployment risk, we find no significant negative impact of higher occupational unemployment risk on grocery spending growth. Specifically, in column 1, using change in unemployment rate as the measure of unemployment risk, we find that the 95% confidence interval of the impact of a one percentage point rise in unemployment risk is -0.136 to 0.135 percentage point change in grocery spending growth. Since this interval includes zero, we cannot reject the null of a zero impact. The absence of a significant impact could be due to predictable volatility of unemployment rates in certain occupations that therefore do not factor into the household's spending/saving decisions. To control for this baseline volatility, in column 2, we use the normalized change in unemployment rate as the measure of unemployment risk. Surprisingly, we do find a small, but significant relationship between unemployment risk and grocery spending growth. A one standard deviation rise in the unemployment

[16] $u_{j,t-12}$ is the unemployment rate of occupation j one year before before an individual's last (fourth) survey, and $u_{j,t-21}$ is the unemployment rate of occupation j one year before an individual's first (first) survey.

risk raises grocery spending growth by 0.45 percentage points. This result is surprising, as it is large and in the opposite direction of the theoretical relationship that we expected. However, the result is only significant at the 95% confidence level.

In column 3, we use our third measure of unemployment risk based on the normalized change in the typical duration of unemployment in an occupation. Using this measure, we find that a standard deviation increase in the unemployment risk results in a change in grocery spending growth between -0.8 and 0.756 percentage points; thus, we cannot reject the null of a zero effect.[17] Finally, in column 4, we consider our last measure of change in unemployment risk based on a combination of changes in the occupational unemployment rate and the average duration of unemployment for an occupation. In column 4, using this measure, we find that a 1 standard deviation increase in the unemployment risk results in a change in grocery spending growth between -0.250 and 1.36 percentage points.

Overall, we find that in the PSID, occupational unemployment risk does not appear to have a large or significant impact on (grocery) spending, but we cannot rule out some effect, as our confidence intervals are fairly wide.

Table 1. PSID: Grocery Spending

	(1) Change in log Grocery Spending	(2) Change in log Grocery Spending	(3) Change in log Grocery Spending	(4) Change in log Grocery Spending
Change in occupational unemployment rate	-0.000867 [-0.136,0.135]			
Normalized change in occupational unemployment rate		0.00455* [0.0000727,0.00902]		
Normalized change in duration of unemployment			-0.000221 [-0.00800,0.00756]	
Normalized combined measure of unemployment risk				0.00555 [-0.00250,0.0136]
Change in log annual income	0.0433*** [0.0298,0.0568]	0.0432*** [0.0296,0.0567]	0.0460*** [0.0247,0.0672]	0.0498*** [0.0278,0.0718]
Constant	-0.182*** [-0.208,-0.156]	-0.178*** [-0.204,-0.152]	-0.00836 [-0.0218,0.00513]	-0.00621 [-0.0194,0.00702]
Observations	50489	50402	19608	18366

Time FE in All Regressions. 95% Confidence Interval in brackets. Outlier values removed. Standard errors clustered on occupation and year

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We next turn to the CEX to determine whether the absence of a relationship between unemployment risk and consumption is a robust finding. As with the PSID, we present the results of four different regressions, each using a different measure of occupational unemployment risk, in the four columns of Table 2. Column 1 suggests that the 95% confidence interval of the impact of a one percentage point year-on-year (YoY) rise in the occupational unemployment rate results in a change in grocery spending growth between -1.242 and 0.13 percentage point. Since this

[17] When using the duration-based measure of risk, we greatly limit the number of years we are able to study in the PSID as the first year for which we can compute the average duration of unemployment for occupations is 1995.

interval includes zero, we cannot reject the null of a zero impact. Column 2 suggests that the 95% confidence interval of the impact of a one standard deviation increase in the normalized change in occupational YoY unemployment rate results in a change in grocery spending growth between -1.24 and .368 percentage point. Unlike in the PSID, in the CEX we find no significant positive relationship between the normalized change in occupational unemployment rate and grocery spending growth. Column 3 suggests that the 95% confidence interval of the impact of a one standard deviation increase in the normalized change in the duration of unemployment for the respondent's occupation results in a change in grocery spending growth between -0.232 and 0.224 percentage point. Finally, Column 4 suggests that the 95% confidence interval of the impact of a one standard deviation increase in the combined measure results in a change in grocery spending growth between -1.77 and 0.160 percentage point.[18]

Overall, we again find that occupational unemployment risk does not appear to have a large or significant impact on spending, but we cannot rule out some effect because our confidence intervals are fairly wide.

In the CEX, even income growth does not appear to have a significant impact on spending growth. One possible explanation for this counterintuitive result is the interview timing structure of the CEX—the income recall period is 12 months while the expenditure recall period is three months. Therefore, the horizon over which the income growth is computed is longer than the horizon of the expenditure growth measure.

Table 2. CEX: Grocery Spending

	(1) Change in log Grocery Spending	(2) Change in log Grocery Spending	(3) Change in log Grocery Spending	(4) Change in log Grocery Spending
Change in YoY	-0.556			
unemployment rate	[-1.242,0.130]			
Normalized		-0.00435		
change in YoY unemployment rate		[-0.0124,0.00368]		
Normalized			-0.0105	
change in duration of unemployment			[-0.0232,0.00224]	
Normalized				-0.00804
combined measure of unemployment risk				[-0.0177,0.00160]
Change in log	-0.00772	-0.00771	-0.0167	-0.0164
last 12 months income	[-0.0323,0.0169]	[-0.0323,0.0169]	[-0.0425,0.00907]	[-0.0422,0.00938]
Constant	-0.0131	-0.0133	-0.0316	-0.0263
	[-0.0896,0.0634]	[-0.0898,0.0632]	[-0.149,0.0855]	[-0.146,0.0935]
Observations	16538	16538	14719	14719

Time FE in All Regressions. 95% Confidence Interval in brackets. Outlier values removed. Standard errors clustered on occupation and year/month
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

It is possible that the workers react to a higher risk of unemployment by changing spending patterns in discretionary categories of expenditure such as leisure rather than necessity categories

[18] Unlike with the PSID, we can also study total spending in the CEX. These results are shown in Appendix 9 in Section A.

of expenditure such as grocery. To test this, we next analyze the impact of occupational unemployment risk on restaurant spending in both the PSID and CEX data. We focus on restaurant spending because it is a common category of spending that easily contrasts with grocery spending and is available for surveys starting in 1969 in the PSID.

Table 3 shows the results using the PSID data. These results are comparable to the analysis with grocery spending in table 1. We find a significant positive relationship between annual income growth and restaurant spending growth. A one percentage point higher annual income growth leads to an increase in restaurant spending growth between 0.0209 and 0.0575 percentage point. We find no significant impact of changes in the occupational unemployment risk on restaurant spending growth. In column 1, a one percentage point higher occupational unemployment rate results in a change in restaurant spending growth between -0.0754 and 0.309 percentage point. In column 2, a one standard deviation rise in the normalized occupational unemployment rate results in a restaurant spending growth change between -0.788 and 0.486 percentage point. In column 3, a one standard deviation increase in the normalized change in the duration of occupational unemployment results in a change in restaurant spending growth between -0.652 and 1.32 percentage points. Finally, in column 4, a one standard deviation increase in the combined measure results in a change in restaurant spending growth between -0.994 and 1.22 percentage points. Overall we continue to find no significant impact of occupational unemployment risk on restaurant spending, but our confidence intervals remain fairly large, so there could still be a smaller effect.

Table 3. PSID: Restaurant Spending

	(1) Change in log Restaurant Spending	(2) Change in log Restaurant Spending	(3) Change in log Restaurant Spending	(4) Change in log Restaurant Spending
Change in occupational unemployment rate	0.117 [-0.0754,0.309]			
Normalized change in occupational unemployment rate		-0.00151 [-0.00788,0.00486]		
Normalized change in duration of unemployment			0.00334 [-0.00652,0.0132]	
Normalized combined measure of unemployment risk				0.00114 [-0.00994,0.0122]
Change in log annual income	0.0392*** [0.0209,0.0575]	0.0386*** [0.0203,0.0570]	0.0489*** [0.0209,0.0769]	0.0456** [0.0167,0.0744]
Constant	0.0272 [-0.0135,0.0679]	0.0295 [-0.0111,0.0700]	-0.00257 [-0.0225,0.0173]	-0.00301 [-0.0236,0.0176]
Observations	40707	40634	16885	15776

Time FE in All Regressions. 95% Confidence Interval in brackets. Outlier values removed. Standard errors clustered on occupation and year

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We undertake a similar analysis of the impact of occupational unemployment risk on food-out spending growth using the CEX data. The results are presented in table 4. As in the PSID, we again find no significant relationship between occupational unemployment risk and spending for all four measures of unemployment risk.

Table 4. CEX: Restaurant Spending

	(1) Change in log Restaurant Spending	(2) Change in log Restaurant Spending	(3) Change in log Restaurant Spending	(4) Change in log Restaurant Spending
Change in YoY unemployment rate	-0.334			
	[-1.329,0.660]			
Normalized change in YoY unemployment rate		-0.00849		
		[-0.0199,0.00290]		
Normalized change in duration of unemployment			0.00464	
			[-0.0127,0.0220]	
Normalized combined measure of unemployment risk				-0.00642
				[-0.0198,0.00699]
Change in log last 12 months income	0.0559**	0.0560**	0.0565**	0.0564**
	[0.0201,0.0917]	[0.0203,0.0918]	[0.0187,0.0942]	[0.0186,0.0941]
Constant	0.0369	0.0335	0.108	0.103
	[-0.0779,0.152]	[-0.0822,0.149]	[-0.0242,0.239]	[-0.0299,0.236]
Observations	13129	13129	11671	11671

Time FE in All Regressions. 95% Confidence Interval in brackets. Outlier values removed. Standard errors clustered on occupation and year/month

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

To further check the robustness of our results, we examine the impact of occupational unemployment risk on several other categories of discretionary spending in the PSID as well as the CEX. These alternative spending measures are typically not available for as many survey years and may also be more difficult for survey respondents to recall accurately, but we consider them nevertheless because occupational unemployment risk may affect different types of spending differently. We consider the impact of occupational unemployment risk on recreation spending in the PSID in Table 5. The confidence intervals are even wider for these alternative spending categories. For example, a one standard deviation increase in the normalized occupational unemployment rate has a 95% confidence interval of a change in recreation spending growth between -0.852 and 3.47 percentage points, compared to a confidence interval between -0.788 and 0.486 percentage points for the change in restaurant spending growth. We find similar results for vacations in Appendix A Table 7.

One issue with the previous categories of the spending that we have analyzed is that survey respondents in the PSID may not accurately recall how much they spent on grocery, restaurant dining, or recreation over the course of the last two years. Therefore, we also consider down payments on cars in the PSID. Since these are likely to be large, infrequent payments, we believe that survey respondents are more likely to recall how much they spent in this category.[19] As shown in Appendix A Table 8, we again find no significant impact of occupational unemployment risk on household spending but with wide confidence intervals.

[19]Note that because most respondents spend \$0 on car down payments in most years, we look at the dollars spent on car down payments instead of the change in log spending. Additionally, we filter outliers slightly differently. We consider individuals spending more than or equal to \$50,000 on a car down-payment as outliers.

Table 5. PSID: Recreation Spending

	(1) Change in log Recreation Spending	(2) Change in log Recreation Spending	(3) Change in log Recreation Spending	(4) Change in log Recreation Spending
Change in occupational unemployment rate	0.368 [-0.0847,0.821]			
Normalized change in occupational unemployment rate		0.0131 [-0.00852,0.0347]		
Normalized change in duration of unemployment			0.0198 [-0.00507,0.0446]	
Normalized combined measure of unemployment risk				0.0252 [-0.00542,0.0558]
Change in log annual income	0.0475* [0.00142,0.0936]	0.0465* [0.000213,0.0929]	0.0538* [0.00574,0.102]	0.0493 [-0.00381,0.102]
Constant	0.0119 [-0.0181,0.0419]	0.0149 [-0.0163,0.0461]	0.0137 [-0.0205,0.0480]	0.0156 [-0.0199,0.0511]
Observations	5916	5893	5264	4401

Time FE in All Regressions. 95% Confidence Interval in brackets. Outlier values removed. Standard errors clustered on occupation and year

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We similarly also analyze the impact of occupational unemployment risk on other forms of spending in the CEX. While exactly corresponding vacation and recreation/entertainment categories do not exist in the CEX, there are other discretionary spending variables that we can use to try and compare to the results from the PSID. We create a "total discretionary spending" variable combining expenditure in the categories for apparel, reading, personal care, television & radio, other entertainment, pets & toy, household expenditure, and miscellaneous expenditure. As shown in Table 6, there is no significant impact of unemployment risk on this combined measure of discretionary spending either. We also look at the impact of occupational unemployment risk on car down payments in the CEX.[20] As shown in Appendix A Table 10, the absence of a significant impact of unemployment risk on spending continues to be a robust finding.

[20]Car spending in the CEX is measured as net outlay—that is, the amount paid for a new car minus the value of any old cars traded in.

Table 6. CEX: Discretionary Spending

	(1) Change in log Discretionary Spending	(2) Change in log Discretionary Spending	(3) Change in log Discretionary Spending	(4) Change in log Discretionary Spending
Change in YoY unemployment rate	-0.599 [-1.733,0.535]			
Normalized change in YoY unemployment rate		-0.00402 [-0.0162,0.00816]		
Normalized change in duration of unemployment			-0.0110 [-0.0296,0.00754]	
Normalized combined measure of unemployment risk				-0.00467 [-0.0189,0.00953]
Change in log last 12 months income	0.0379* [0.00145,0.0744]	0.0380* [0.00148,0.0745]	0.0355 [-0.00334,0.0744]	0.0361 [-0.00281,0.0749]
Constant	-0.195*** [-0.264,-0.126]	-0.195*** [-0.265,-0.125]	-0.188* [-0.365,-0.0107]	-0.182* [-0.361,-0.00172]
Observations	13485	13485	11988	11988

Time FE in All Regressions. 95% Confidence Interval in brackets. Outlier values removed. Standard Errors Clustered on Occupation and Year/Month

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

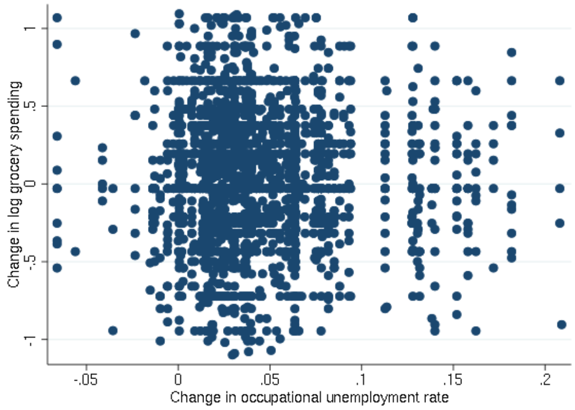
4.1 Great Recession

Based on our previous regression results, it appears that fluctuations in occupational unemployment risk are not significant drivers of household spending decisions. It is possible that households react to occupational unemployment risk only when the shock is significant enough. Additionally, during a significant recession households may pay more attention or have easier access to unemployment information about their own occupations, enabling them to more accurately gauge their occupational unemployment risk.To test this theory, we look at the relationship between unemployment risk and expenditure growth in both the CEX and PSID data during the Great Recession. We choose the Great Recession because it is the largest shock to unemployment over the period for which CEX and PSID data are available. If individuals react to changes in occupational unemployment risk, we expect to observe it during this 2008–2009 time period. Additionally, instead of taking a regression approach with a sample limited to this time period, we instead look at scatter plots during this time to see if, without controlling for any other variables, an association exists between occupational unemployment risk and consumption spending.

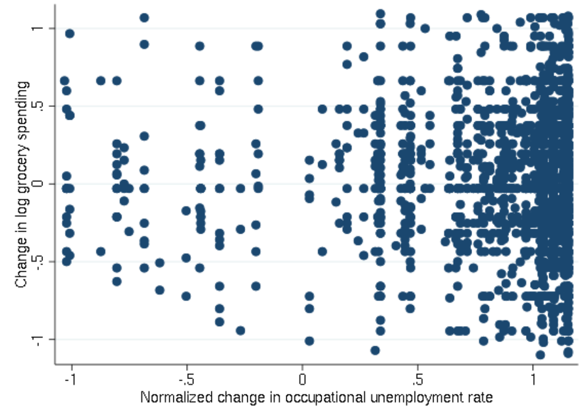
We first focus on all PSID respondents in the year 2009. To visualize the impact at the start of the Great Recession, we create scatter plots[21] of change in unemployment risk against spending growth in 2009 relative to 2007. (We omit 2008 as there was no PSID survey that year). Figure 1 shows that there is no apparent correlation between unemployment risk and grocery spending in the PSID even during the Great Recession. This suggests that if individuals react to higher unemployment risk by changing their spending, the impact is small enough as to not be visible in the data during a significant shock. There is similarly no apparent correlation between unemployment risk and restaurant spending during the Great Recession (Figure 2).

[21]We restrict the sample in the same way as the main empirical analysis to remove outliers and to try to ensure that households remain comparable from one period to the next.

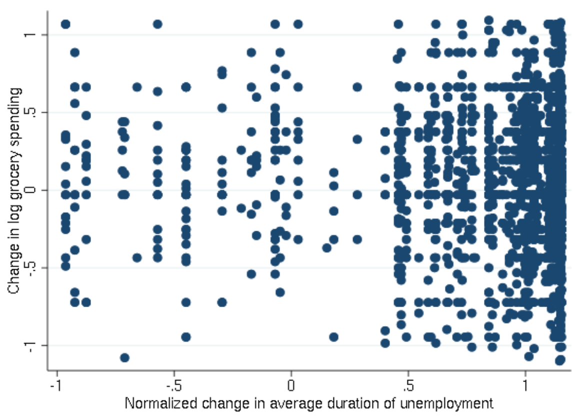
Figure 1. PSID: Grocery Spending during Great Recession



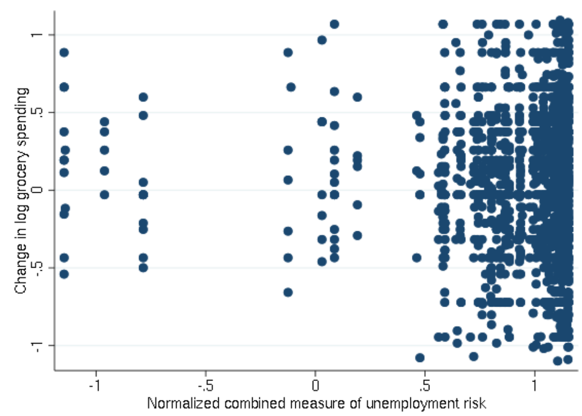
(a) Change in Occupational Unemployment Rate



(b) Normalized Change in Occupational Unemployment Rate

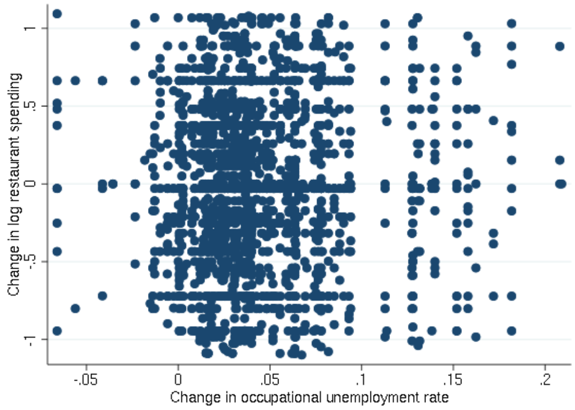


(c) Average Duration of Unemployment per Occupation



(d) Normalized Combined Measure of Unemployment Risk

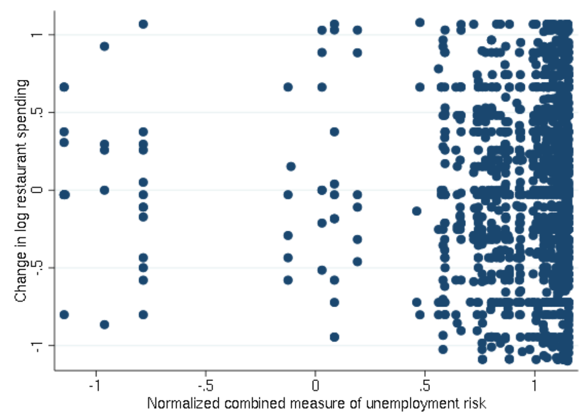
Figure 2. PSID: Restaurant Spending during Great Recession



(a) Change in Occupational Unemployment Rate

(b) Normalized Change in Occupational Unemployment Rate

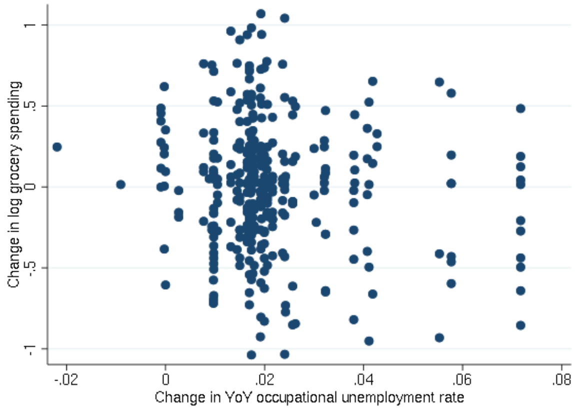
(c) Average Duration of Unemployment per Occupation



(d) Normalized Combined Measure of Unemployment Risk

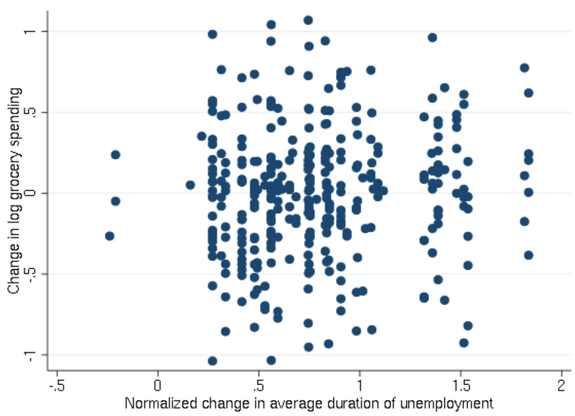
We also look at similar scatter plots using data from the CEX. We focus on the cohort of individuals whose first interview fell between July and October 2008 and whose fourth interview fell between April and July 2009. Therefore, the change in spending between these respondents' first and fourth interviews represents their change in pre- and post-Great-Recession spending. In Figure 3 and Figure 4, we are again unable to detect any correlation between our four measures of occupational unemployment risk and either grocery spending or restaurant spending. In Appendix A we show that this lack of an association also holds for total spending and discretionary spending in Figure 5 and Figure 6. These results are consistent with our corresponding findings in the PSID.

Figure 3. CEX: Grocery Spending during Great Recession

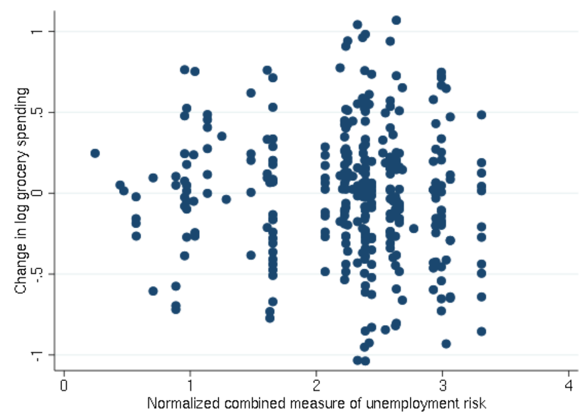


(a) Change in Occupational Unemployment Rate

(b) Normalized Change in Occupational Unemployment Rate

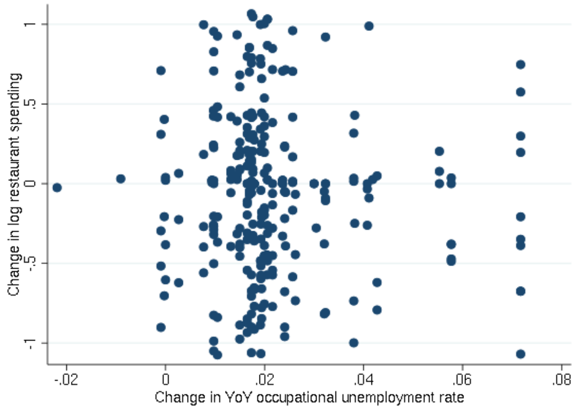


(c) Average Duration of Unemployment per Occupation

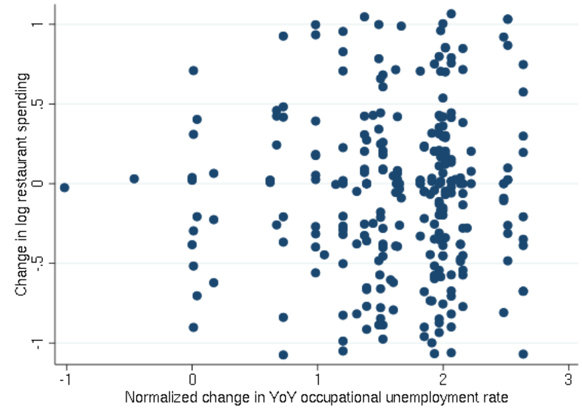


(d) Normalized Combined Measure of Unemployment Risk

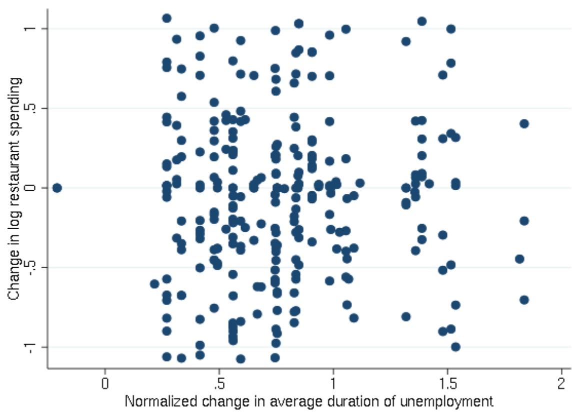
Figure 4. CEX: Restaurant Spending during Great Recession



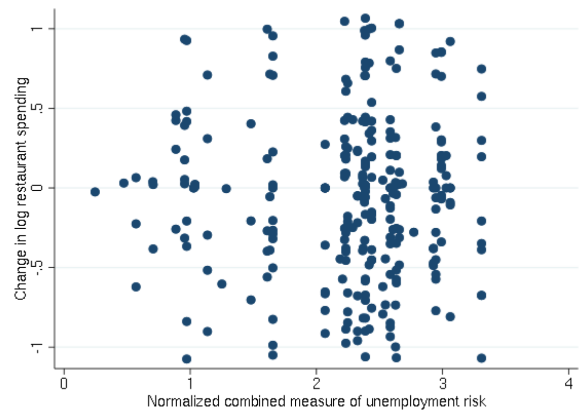
(a) Change in Occupational Unemployment Rate



(b) Normalized Change in Occupational Unemployment Rate



(c) Average Duration of Unemployment per Occupation



(d) Normalized Combined Measure of Unemployment Risk

5 Conclusion

We explore whether workers respond to greater risk of occupational unemployment by cutting their spending (or increasing their savings) as predicted by the life-cycle consumption and precautionary savings hypotheses. We employ multiple measures of risk, using multiple decades of data, across multiple surveys and spending categories. We consistently find that occupational unemployment risk does not have a significant impact on spending decisions. That being said, it is important to note that despite using four different unemployment risk measures and considering two different surveys, we are unable to reject the possibility of a smaller effect of occupational unemployment risk on consumption because the confidence intervals for our results remain wide. We also find no evidence of a relationship between occupational unemployment risk and household spending during the Great Recession during which some occupations experienced large increases in unemployment.

There are potential explanations for why household spending may not react a lot to changes in occupational unemployment risk. Individuals may gauge unemployment risk based not on occupational factors but on either aggregate unemployment or their own personal employment circumstances, which are not accurately captured by occupational unemployment information. For example, when forming perceptions of future unemployment risk, workers may pay attention to factors such as the performance of their firm or their own relative performance within the firm, and they may ignore broader factors such as what is happening to other workers in their occupation. This might explain why, using data from the PSID, Hendren (2017) finds that individuals who eventually become unemployed cut their food spending in the year(s) preceding actual unemployment. Whereas measuring unemployment risk at the occupational level, we find no significant impact of higher risk on food spending. It is also possible that individuals only pay attention to occupational unemployment risk in extremely specific scenarios. Juelsrud and Wold (2019) and Fuchs-Schündeln and Schündeln (2005) both highlight very unique situations where significant macroeconomic changes were widely known to differentially impact specific occupations. This contrasts with our generalized approach of looking at all occupations over a long period of time. Also, even during the Great Recession, the relative impacts on different occupations may not have been clear at the time. We hope our results clarify that even in the face of large unemployment shocks, household spending is unlikely to change a great deal in response to occupational unemployment risks alone.

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Appendices

A Additional Results

Table 7. PSID: Vacation Spending

	(1) Change in log Vacation Spending	(2) Change in log Vacation Spending	(3) Change in log Vacation Spending	(4) Change in log Vacation Spending
Change in occupational unemployment rate	-0.194 [-0.574,0.187]			
Normalized change in occupational unemployment rate		0.00356 [-0.0147,0.0218]		
Normalized change in duration of unemployment			0.00710 [-0.0151,0.0293]	
Normalized combined measure of unemployment risk				-0.00428 [-0.0313,0.0227]
Change in log annual income	0.0661*** [0.0287,0.104]	0.0673*** [0.0299,0.105]	0.0730*** [0.0352,0.111]	0.0722*** [0.0327,0.112]
Constant	0.0266* [0.00240,0.0508]	0.0292* [0.00412,0.0542]	0.0210 [-0.00664,0.0485]	0.0154 [-0.0128,0.0436]
Observations	5982	5965	5331	4459

Time FE in All Regressions. 95% Confidence Interval in brackets. Outlier values removed. Standard errors clustered on occupation and year

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8. PSID: Car Down Payment Spending

	(1) Amount Paid Car Down Payments	(2) Amount Paid Car Down Payments	(3) Amount Paid Car Down Payments	(4) Amount Paid Car Down Payments
Change in occupational unemployment rate	-239.1 [-3879.2,3401.1]			
Normalized change in occupational unemployment rate		28.27 [-159.8,216.3]		
Normalized change in duration of unemployment			88.87 [-83.34,261.1]	
Normalized combined measure of unemployment risk				69.26 [-146.3,284.8]
Change in log annual income	-81.63 [-387.3,224.0]	-73.57 [-380.3,233.2]	-34.72 [-345.9,276.5]	-35.31 [-367.2,296.5]
Constant	2525.4*** [2108.8,2942.0]	2534.8*** [2111.7,2957.9]	2427.5*** [1991.6,2863.4]	2426.3*** [1978.6,2873.9]
Observations	15284	15231	13761	12425

Time FE in All Regressions. 95% Confidence Interval in brackets. Outlier values removed. Standard errors clustered on occupation and year

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9. CEX: Total Spending

	(1) Change in log Total Spending	(2) Change in log Total Spending	(3) Change in log Total Spending	(4) Change in log Total Spending
Change in YoY unemployment rate	-0.326			
	[-0.895,0.242]			
Normalized change in YoY unemployment rate		0.000342		
		[-0.00653,0.00721]		
Normalized change in duration of unemployment			-0.00773	
			[-0.0188,0.00336]	
Normalized combined measure of unemployment risk				-0.00207
				[-0.0105,0.00635]
Change in log last 12 months income	0.106***	0.106***	0.110***	0.110***
	[0.0846,0.127]	[0.0846,0.127]	[0.0882,0.132]	[0.0884,0.132]
Constant	-0.0593	-0.0578	0.0640	0.0690
	[-0.140,0.0214]	[-0.139,0.0230]	[-0.0412,0.169]	[-0.0379,0.176]
Observations	16785	16785	14931	14931

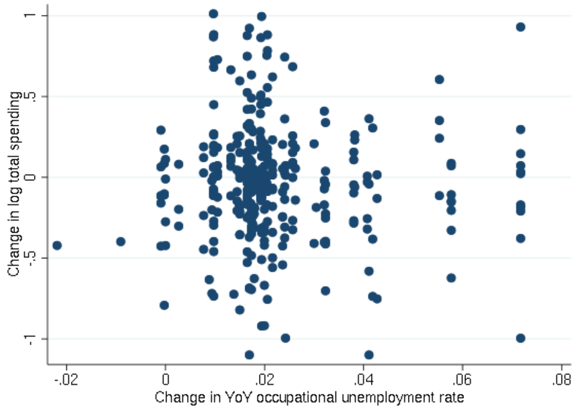
Time FE in All Regressions. 95% Confidence Interval in brackets. Outlier values removed. Standard Errors Clustered on Occupation and Year/Month
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10. CEX: Car Spending

	(1) Change in new Car/Truck Spending (net outlay)	(2) Change in new Car/Truck Spending (net outlay)	(3) Change in new Car/Truck Spending (net outlay)	(4) Change in new Car/Truck Spending (net outlay)
Change in YoY unemployment rate	617.3			
	[-1971.8,3206.3]			
Normalized change in YoY unemployment rate		14.80		
		[-19.92,49.52]		
Normalized change in duration of unemployment			39.09	
			[-11.56,89.75]	
Normalized combined measure of unemployment risk				28.05
				[-12.08,68.18]
Change in log last 12 months income	82.98	82.76	65.67	64.66
	[-6.518,172.5]	[-6.759,172.3]	[-25.76,157.1]	[-26.73,156.1]
Constant	289.6	295.5	156.4	136.2
	[-261.0,840.2]	[-255.2,846.2]	[-85.96,398.8]	[-103.5,376.0]
Observations	17390	17390	15457	15457

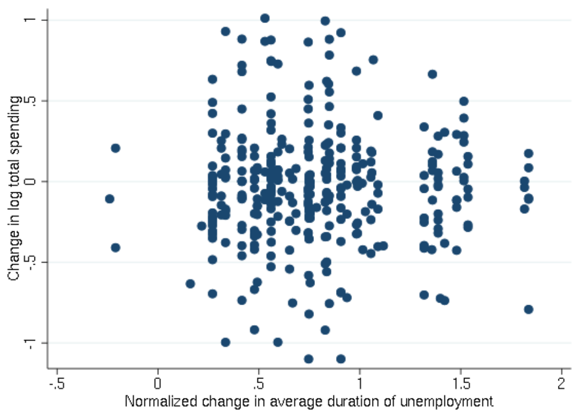
Time FE in All Regressions. 95% Confidence Interval in brackets. Outlier values removed. Standard errors clustered on occupation and year/month
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 5. CEX: Total Spending during Great Recession

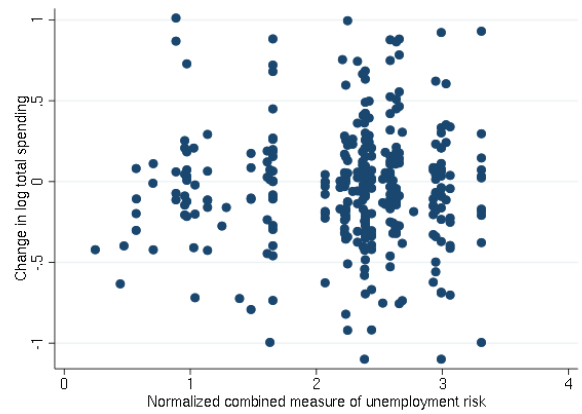


(a) Change in Occupational Unemployment Rate

(b) Normalized Change in Occupational Unemployment Rate

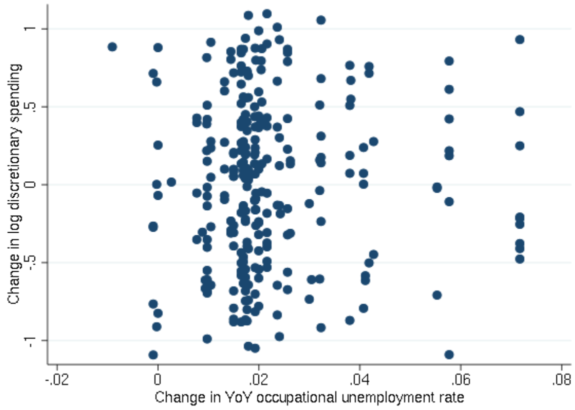


(c) Average Duration of Unemployment per Occupation

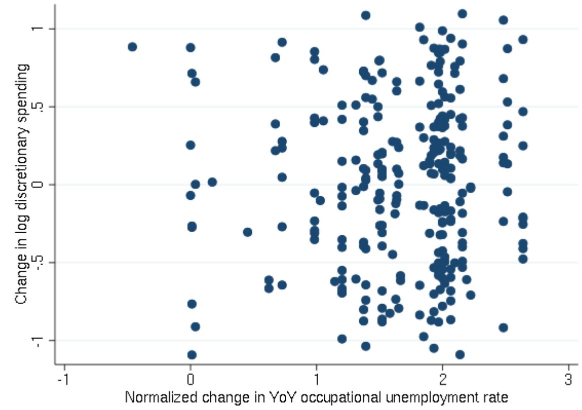


(d) Normalized Combined Measure of Unemployment Risk

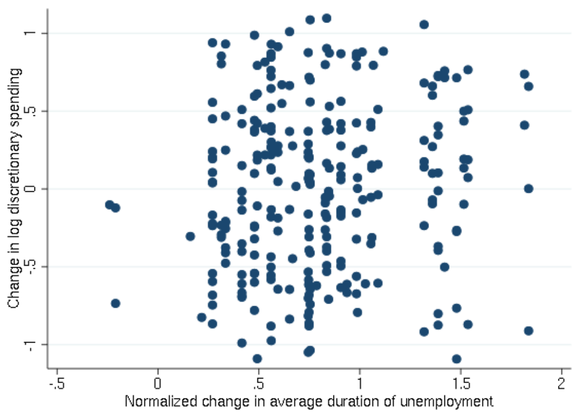
Figure 6. CEX: Discretionary Spending during Great Recession



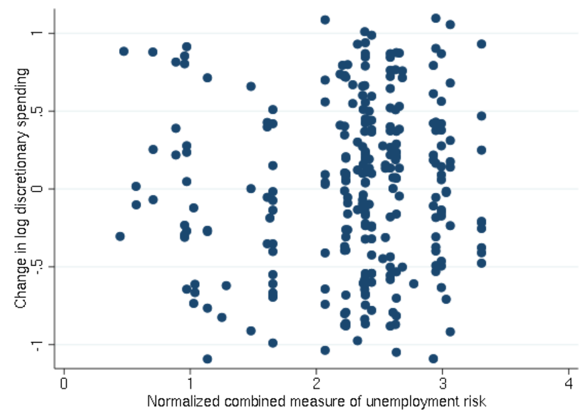
(a) Change in Occupational Unemployment Rate



(b) Normalized Change in Occupational Unemployment Rate



(c) Average Duration of Unemployment per Occupation



(d) Normalized Combined Measure of Unemployment Risk

B Industry as a Measure of Unemployment Risk

One additional topic we investigated was whether or not industry could also be used as a measure for unemployment risk in the same way that we used occupation. One immediate issue that comes with doing this is that there is no question in the CEX which asks about an individual's industry. Thus, when considering industry we are limited to only data from the PSID. Luckily, using CPS-ASEC data we are able to calculate unemployment by industry as well. However, the same issue exists with industry as occupation, where the Census Industry Coding Scheme used in the PSID and CPS have changed over time. To solve this issue we once again use harmonized codes available from IPUMS-CPS. Whereas with occupation we used a combination on occ1990 and occ2010 harmonized codes, with industry we only use ind1990 as there is not equivalent set of ind2010 codes. Additionally, as with occupation, we exclude industry "switch years" where either the PSID or CPS-ASEC switched the industry classification scheme they were using (see Section C to see the exact year). Lastly, as with occupation, there are still some harmonized industry codes with less than 100 responses per year in the CPS-ASEC. In order to ensure the accuracy of our industry-based unemployment risk measures, we exclude these harmonized industries with less than 100 respondents.

We can then create two new measures of unemployment risk the normalized/non-normalized change in the industrial unemployment rate (see Section D.2 to see period used for normalizing the change in industrial unemployment rates). Using these two new measures we can recreate the same PSID regressions as with occupation, comparing the impact of industry-based unemployment risk on food spending. As you can see in Table 11, these results by industry largely resemble what we saw with occupation. Across all four regressions we see a significantly positive relationship between income and spending. Additionally, across all four regressions we see no significant negative relationships between unemployment risk and spending. However, we do see in Table 11 column 2 that when we used the normalized change in unemployment per industry as our measure of unemployment risk, there is a slightly significant positive relationship been unemployment risk and grocery spending. Such a relationship would be quite surprising, as it is unlikely that as the risk on unemployment increases so does spending. More likely this is a spurious relationship between these two variables. Additionally, we see in regression four, that when we look at restaurant instead of grocery, no such positive relationship exists. Based on these results, it appears as if no meaningful relationship exists between spending and our measures of industry-based unemployment risk. However, because we are unable to validate this result in the CEX, we conclude our investigation of industry-based unemployment

Table 11. PSID: Grocery Spending vs Restaurant Spending, Unemployment by Industry

	(1) Change in log Grocery Spending	(2) Change in log Grocery Spending	(3) Change in log Restaurant Spending	(4) Change in log Restaurant Spending
Change in	0.0358		0.0247	
industrial unemployment rate	[-0.107,0.179]		[-0.168,0.217]	
Normalized		0.00534*		-0.000473
change in industrial unemployment rate		[0.00104,0.00964]		[-0.00643,0.00548]
Change in log	0.0441***	0.0442***	0.0392***	0.0388***
annual income	[0.0307,0.0575]	[0.0307,0.0576]	[0.0221,0.0564]	[0.0216,0.0560]
Constant	-0.178***	-0.176***	0.0266	0.0271
	[-0.198,-0.158]	[-0.196,-0.156]	[-0.0139,0.0670]	[-0.0134,0.0675]
Observations	53243	53085	42966	42843

Time FE in All Regressions. 95% Confidence Interval in brackets. Outlier values removed. Standard errors clustered on industry and year

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

C Switch Years in CPS/PSID

C.1 CPS Switch Years – Occupation

- 1968: CPS begins using the 1960 Census Occupation Codes
- 1972: CPS begins using the 1970 Census Occupation Codes
- 1983: CPS begins using the 1980 Census Occupation Codes

- 1992: CPS begins using the 1990 Census Occupation Codes
- 2003: CPS begins using the 2000 Census Occupation Codes
- 2011: CPS begins using the 2010 Census Occupation Codes

C.2 CPS Switch Years – Industry

- 1971: CPS begins using the 1960 Census Industry Codes
- 1983: CPS begins using the 1970 Census Industry Codes
- 1992: CPS begins using the 1980 Census Industry Codes
- 2003: CPS begins using the 2002 Census Industry Codes
- 2009: CPS begins using the 2007 Census Industry Codes

C.3 PSID Switch Years

- 1968: Start of the PSID originally, used two-digit occupation/industry codes until 1981; however, in retrospective coding project three-digit 1970 Census Occupation/Industry Codes were assigned back to 1968.
- 1981: PSID originally started using 1970 Census Occupation/Industry Codes.
- 2003: PSID switches to using the 2000 Census Occupation/Industry Codes
- 2017: PSID switches to using the 2010 Census Occupation Codes and 2012 Industry Codes

D Normalization Periods

D.1 Periods in PSID – Occupation

- Period 1: 1969-1971 (1960 Occupation Codes used in CPS)
- Period 2: 1973-1982 (1970 Occupation Codes used in CPS)
- Period 3: 1984-1991 (1980 Occupation Codes used in CPS)
- Period 4: 1993-2002 (1990 Occupation Codes used in CPS)
- Period 5: 2004-2010 (2000 Occupation Codes used in CPS)
- Period 6: 2012-2016 (2010 Occupation Codes used in CPS)

D.2 Periods in PSID – Industry

- Period 1: 1969-1971 (1960 Industry Codes used in CPS)
- Period 2: 1972-1982 (1970 Industry Codes used in CPS)
- Period 3: 1984-1991 (1980 Industry Codes used in CPS)
- Period 4: 1993-2002 (1990 Industry Codes used in CPS)
- Period 5: 2004-2008 (2002 Industry Codes used in CPS)
- Period 6: 2010-2013 (2007 Industry Codes used in CPS)

D.3 Periods in CEX

- Period 1: 1996-2002 (1990 Occupation Codes used in CPS)
- Period 2: 2003-2010 (2000 Occupation Codes used in CPS)
- Period 3: 2011-2018 (2010 Occupation Codes used in CPS)

E Years Available

E.1 PSID

- Grocery Spending
  - 1968-1972
  - 1974-1987
  - 1990-2017
- Annual Income
  - 1968-2017
- Restaurant Spending
  - 1969-1972
  - 1974-1987
  - 1990-2017
- Vacation Spending
  - 2005-2017
- Recreation/Entertainment Spending
  - 2005-2017

- Car Down Payment Spending
  - 1999-2019

E.2 CEX

- Total Expenditure
  - 1996-2018
- Last 12-Months Income
  - 1996-2004
  - 2006-2018
- Discretionary Expenditure
  - 1996-2018
- Personal Care Expenditure
  - 1996-2018
- Apparel Expenditure
  - 1996-2018
- Grocery Expenditure
  - 1996-2018
- Restaurant Expenditure
  - 1996-2018
- Car/Truck Expenditure
  - 1996-2018