Heterogeneous Consumers and Fiscal Policy Shocks

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Abstract: This paper studies empirical facts regarding the effects of unexpected changes in aggregate macroeconomic fiscal policies on consumers that are allowed to differ depending on their individual characteristics. We use data from the Consumption Expenditure Survey (CEX) to estimate individual-level impulse responses as well as multipliers for government spending. The main empirical finding of this paper is that unexpected fiscal shocks have substantially different effects on consumers depending on their income and age levels. In particular, the wealthiest individuals tend to behave according to the predictions of standard RBC models, whereas the poorest individuals tend to behave according to standard IS-LM (non-Ricardian) models, most likely due to credit constraints. Furthermore, government spending policy shocks tend to decrease consumption inequality.

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1 Introduction

Most of the literature studying the effects of fiscal policy shocks relies on the representative agent paradigm. The assumption of a representative agent is generally made for technical simplicity, since the solution of dynamic models with heterogeneous agents is computationally challenging. However, the study of aggregate data might provide the incorrect evaluation of economic theories. For example, Attanasio and Weber (1993) demonstrate that the use of microeconomic data can overturn rejections of consumer intertemporal optimization models based on aggregate data. In addition, the assumption comes at the cost of preventing the analysis of important questions such as whether economic policies equally affect individuals with different characteristics, whether they influence inequality, or what are the macroeconomic consequences of aggregate fluctuations on the welfare of individuals that differ in their consumption patterns. In other words, while the representative agent assumption allows macroeconomists to study how average values of macroeconomic variables are affected by economic policies, it does not allow them to study how these policies affect the distribution of such variables across households.

This paper focuses on studying the effects of unexpected changes in aggregate fiscal policies on consumers that are allowed to differ depending on their individual characteristics. We ask the questions: "Do fiscal shocks affect individuals differently? And, if so, how?". Fiscal policy analysis is an especially important area of macroeconomics since it has direct implications for consumers’ welfare.\(^1\) The literature has extensively studied the effects of government spending and tax policy shocks on aggregate macroeconomic variables; one of the approaches, which we focus on, has been narrative – see Ramey and Shapiro (1998) and Ramey (2009, 2011a).\(^2\) The narrative approach uses narrative records (such as presidential speeches and newspapers) to identify the timing and magnitude of major fiscal changes, and identifies fiscal shocks as those changes that were taken for reasons exogenous to the business

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\(^1\) Although our paper does not directly provide a welfare analysis, it provides an analysis of the effects of fiscal policy "shocks" on one of the most important consumers' variables, namely their consumption.

cycle. However, since these analyses focus on aggregate data, by construction they only provide an estimate of the average response of aggregate macroeconomic variables to fiscal shocks (on average across individuals), while being uninformative regarding heterogeneity across individual responses. Realistically, fiscal shocks may affect individuals differently depending on their individual-specific characteristics, such as income and age. Studying whether this is the case, and who gains and who loses from unexpected changes in government spending policy is the main focus of this paper. An additional benefit of using household level data besides analyzing heterogeneity is that we can avoid the so-called “aggregation bias”, unavoidable in aggregate data where researchers have no control over the aggregation process. We evaluate the empirical importance of the aggregation bias and analyze its implications for the analysis of fiscal policy shocks on aggregate behavior.

The main empirical finding of this paper is that unexpected government spending shocks have substantially different effects on consumers depending on their income and age levels. Our empirical evidence is based on a narrative approach, and in particular a Vector Autoregressive (VAR) model, as in Ramey (2011a). By using a Structural VAR model where the shock is ordered first, we ensure that the shock series is orthogonal to past information contained in the other variables included in the VAR; at the same time, we allow variables other than the shock to contemporaneously react to the shock itself. Our main finding is that individuals whose consumption levels are most negatively affected by a government spending policy shock (i.e. an unexpected increase in government spending) are the wealthiest and working-age individuals, whereas consumption of the poorest increases the most. Thus, positive government spending policy shocks tend to decrease consumption inequality.

Regarding the economic interpretation of our results, our paper is very related to Galí et al. (2006). Galí et al. (2006) show that a calibrated Keynesian model with sticky prices and rule-of-thumb consumers can generate an increase in consumption when government spending increases. Our results provide further empirical support to the analysis in Gali et al. (2006) by showing that the poorest individuals, i.e. the ones that are more likely to be credit constrained, have a positive consumption response to fiscal policy shocks; on the

other hand, the richest individuals’ consumption responds negatively. Overall, the response of the whole population will depend on which of the two prevails. Other related papers include Schmitt-Grohe’ and Uribe (2010), who study the contribution of anticipated shocks to business cycles in US data, including government spending, and Zubairy (2011), who develops a DSGE model where deep habits generate a positive response of consumption to a positive government spending shock.

This paper’s analysis is closely related to the large literature on the effects of government spending on macroeconomic aggregates, such as Ramey (2009, 2011a). While this literature focuses on the effects of shocks on aggregate data, we focus instead on effects on individual consumption by allowing individuals to be heterogeneous. Our research is also very related to Owyang and Zubairy (2009) and Nekarda and Ramey (2011); the former analyze the effects of government spending shocks on state-level personal income and employment, and find regional patterns in the way government spending policy shocks affect state-level variables. The latter study the effects of government purchases at the industry level. The difference between our paper and theirs is that we focus on heterogeneity across individual consumers, whereas Owyang and Zubairy (2009) focus on heterogeneity across states and Nekarda and Ramey (2011c) across industries.

Our paper is also related to the recent advances in the study of heterogeneity across individuals. After a draft of this paper was circulated, we became aware of work by De Giorgi and Gambetti (2012), who also study the effects of government spending on the distribution of consumption. De Giorgi and Gambetti (2012) study the effects of government spending shocks across income deciles in a VAR that includes Ramey’s (2011) shock as well as the common components of the distribution of CEX consumption across income deciles explained by macroeconomic factors. The factors are extracted from a large dataset of macroeconomic variables. They find empirical results similar to ours, that is, consumption increases for the poorest individuals and decreases for rich individuals, while the middle of the distribution responds very little. While the empirical results are similar, their estimation technique substantially differs from ours; furthermore, they do not consider deciles of the distribution based on other characteristics such as age, which we instead investigate.
Heathcote, Storesletten and Violante (2009) review the theoretical literature on quantitative macroeconomic models with household heterogeneity; our paper instead is an empirical paper that estimates whether heterogeneity in responses to policy shocks is important.\footnote{Theoretical papers on heterogeneous agents models also include Rios-Rull (1995), Krusell and Smith (1998), Heathcote (2005), among others. The latter papers have theoretically developed and calibrated heterogeneous agents models, whereas our focus is on the empirical estimation of the effects of fiscal policy shocks.} Other empirical studies have also become available since the first version of our paper. In particular, Giavazzi and McMahon (2012) study heterogeneity in household responses in hours worked to shifts in fiscal policy. They identify state-specific variation in military contracts driven by aggregate changes in US military spending, which is their measure of fiscal shocks. We instead analyze heterogeneity in household responses to aggregate fiscal shocks identified via a narrative approach in a VAR setting.

The paper is organized as follows. Section 2 describes the data while Section 3 describes the VAR we estimate. Sections 4 and 5 present the empirical results; Section 6 discusses robustness to various VAR specifications and Section 7 concludes.

## 2 Data Description

We collect information on consumption and income heterogeneity across individuals by using household consumption expenditure data from the interview portion of the Consumer and Expenditure Survey (CEX), conducted by the Bureau of Labor Statistics. The measure of government spending shocks we use is the time series developed by Ramey (2011a). We use quarterly data that span 1984:Q1-2008:Q4; the starting date of the sample is determined by the availability of CEX data, whereas the end date is determined by the availability of data on the government spending shocks.\footnote{Although it is possible to find CEX data back to 1980Q1, there are issues regarding the quality and the treatment of the additional data, so we decided to use data starting in 1984Q1.} This section provides a detailed description of the data as well as preliminary data analyses that establish the usefulness of the CEX database for our purposes. In particular, we demonstrate that existing empirical results in the literature are consistent with those based on aggregate CEX data. However, CEX data
have the important advantage of being suitable for more disaggregate analyses, which we undertake in the following sections.

Regarding CEX data, we follow Lusardi (1996) and focus on nondurable consumption defined as expenditures on food, alcoholic beverages, tobacco, utilities, personal care, household operations, public transportation, gas and motor oil, and miscellaneous expenses. We focus on nondurable consumption rather than durable because the latter is more similar to an investment decision. For our measure of income, we use the household’s income after taxes for the 12 months before the survey is taken. The household is identified with the head of the household. We drop households with missing data or non-positive consumption or income data. Also, we drop the 1986:Q1 observation due to missing data. An additional concern is the presence of measurement error in the data, in particular for income data reported in the CEX (Lusardi, 1996). Our procedure involves constructing pseudo-panels by averaging individuals belonging to groups identified by individual-specific characteristics; thus, our procedure attenuates idiosyncratic measurement error by averaging individual-level consumption data. Individual-level income data, which are subject to stronger measurement error, are used only to construct income quintiles, thus not raising strong concerns about the effects of measurement error in income in our main results.

Our measure of consumption is the log of real per capita consumption expenditures. To construct this measure, first we seasonally adjust the data by using the X-12 ARIMA seasonal adjustment procedure of the US Census Bureau. We also divide CEX household data by the number of family members for each household to get a measure of per capita consumption. Finally, we transform CEX consumption in real terms using the nondurables price deflator, as in Ramey (2011a).

We study the effects of government spending identified via a narrative approach. The main advantage of using the narrative approach relative to identifying shocks via a Structural VAR is that the shock is directly identified by using information outside the VAR estimation, and hence does not depend on which variables are included in the VAR or which identifying assumptions are made. The disadvantage of the narrative approach is that it

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6Our empirical results are similar and even stronger when we consider seasonal adjustment based on a moving average. Details are reported in a Not-for-Publication Appendix.
requires judgment calls when creating the shock variable. To mitigate the latter concern, we use already established measures and we include the shocks measures in a Structural VAR to ensure that the shock we use in the empirical analysis is uncorrelated with past values of the other macroeconomic variables we consider.

The measure of government spending policy shocks we use is developed by Ramey (2011a). Typically, when studying government spending policy researchers use defense news shocks since they are the least likely to crowd out private consumption and be affected by demographic changes or the state of the economy. Ramey (2011a) does provide a narrative time series of defense spending news shocks based on studying articles in news sources such as *Business Week* magazine. Unfortunately, Ramey (2011a) shows that the defense news shock does not have good explanatory power for real government spending in the sample period we are working with, which is constrained by the availability of data in the CEX. Ramey (2011a) develops an alternative narrative measure of government defense spending shocks based on the Survey of Professional Forecasters (SPF). The SPF shock is the difference between actual real government spending growth and the SPF’s forecasted growth. She shows that this measure does have good explanatory power for government spending in the time period that we consider, so we focus on this measure in our paper.

It is important to verify that CEX data are appropriate for our analysis, and that using aggregate CEX data does not invalidate fundamental empirical findings in the existing literature. It is also important to verify that our VAR specification is suitable for the analysis even though it includes fewer variables than in Ramey (2011a), due to concerns about parameter proliferation and its negative effects in small samples on VAR estimation with a large number of endogenous variables. We demonstrate that this is the case by comparing aggregate CEX data results with those in Ramey (2011a), which are based on the National Income and Product Accounts (NIPA) data. Although Slesnick (1992, 1998) offers some empirical evidence that the CEX data and the personal consumption expenditure data from the NIPA do not necessarily measure the same quantities, their correlation is substantial (Attanasio, 1998). Furthermore, we are concerned mainly about responses to policy shocks, which might be less affected by differences in the levels of the variables.
We start by replicating Ramey’s (2011a) results with her database for the sub-sample we consider.\textsuperscript{7} To transform aggregate consumption and government spending data in per capita terms, we use population data from the United States Census.\textsuperscript{8} We consider a basic Structural VAR (SVAR) specification inspired by Ramey (2011a):

\[
A(L)Z_t = K + D_1 t + D_2 t^2 + U_t
\]  

(1)

where \(Z_t\) is a vector containing the SPF shock, the log of real per capita total government spending and the log of real per capita aggregate consumption, \(A(L) = A_0 + A_1 L + ... + A_4 L^4\), \(L\) is the lag operator, \(K\) is a vector of constants and \(U_t\) is a vector of shocks identified via the recursive ordering procedure, where the SPF shock is ordered first, and consumption last. In our benchmark results, we let \(D_1 = D_2 = 0\), as requested by a referee; however, we also discuss results with the quadratic trend, which was included in Ramey’s (2011a) original VAR specification. Our VAR is similar to Ramey (2011a) except that she also includes an average tax rate variable and an interest rate variable (we do not include the latter in order to keep our VAR parsimonious, due to small sample concerns).\textsuperscript{9} By using a Structural VAR model where the shock is ordered first, we ensure that the shock series is orthogonal to past information contained in the other variables included in the VAR; at the same time, we allow variables other than the shock to contemporaneously react to the shock itself. We replicate the analysis in Ramey (2011a) by using exactly her aggregate variables, time periods and number of lags (four). The main difference is that we replace her measures of aggregate nondurable consumption from NIPA with our measure of CEX aggregate nondurable consumption. Figure 1, Panel A, reports impulse responses of nondurables consumption to a government spending shock estimated from eq. (1) using aggregate NIPA data in the VAR

\textsuperscript{7}Ramey’s (2011a) sample period is 1947-2008, while ours is 1984-2008. We cannot extend our sample further back due to shorter sample of data available for CEX data.

\textsuperscript{8}The NIPA defines the population as the total population of the United States including the Armed Forces overseas and the institutionalized population. See page 14 in the \textit{A Guide to the National Income and Product Accounts of the United States} located at http://www.bea.gov/national/pdf/nipaguid.pdf.

\textsuperscript{9}The objective of this exercise is to verify that, even in parsimonious VARs and a different sample period, we obtain results similar to Ramey (2011a). For example, we do not include a measure of monetary policy even though it might be important in principle – see Rossi and Zubairy (2011) and Davig and Leeper (2011). The robustness section investigates results for VARs that include additional explanatory variables.
without trend; Figure 2, Panel A, reports results for the VAR with trend. The figures show that the impulse response for nondurables has a very similar shape to Ramey (2011a, Fig. XII). Both our response and Ramey’s are negative on impact as well as a few quarters after the shock. Thus, our results match Ramey’s (2011a) results fairly well. Panel B in Figures 1 and 2 consider instead using aggregate CEX consumption data in place of consumption from NIPA. CEX aggregate consumption is constructed the same way as the NIPA consumption aggregate, that is:

\[ C_t \equiv \ln \left( \frac{1}{H_t} \sum_{i=1}^{H_t} c_{i,t} \right), \]  

(2)

where \( c_{i,t} \) is consumption attributed to individual \( i \) at time \( t \) in the CEX survey, and \( H_t \) is the number of individuals in the survey at time \( t \). It is clear that the responses are both negative and significant, and, although quantitatively different, similar in magnitude.\(^{10}\) Note that the magnitude of the response is different from Ramey’s (2011a); the Not-for-Publication Appendix demonstrates that one of the main reasons behind the differences is that we focus on a different sample\(^ {11}\) (although the confidence bands around our responses include Ramey’s response).

Furthermore, we report peak multipliers. The multipliers are calculated as follows. The peak multiplier is: \( \max_h \left| \frac{\partial \ln C_{t+h}}{\partial \ln G_t} \right| \left| \frac{C_t}{\bar{C}} \right| \text{sign} \left( \frac{\partial \ln C_{t+h}}{\partial \ln G_t} \right) \left( \frac{\partial \ln C_{t+h}}{\partial \ln G_t} \right) \), where \( C_t \) is aggregate consumption at time \( t \), \( G_t \) is government spending and \( \bar{G} \) and \( \bar{C} \) are the average government spending and consumption values over the entire time series. Furthermore, we normalize the impact response of \( G_t \) to the fiscal policy shock to be unity, so we can interpret the impulse-responses of consumption at horizon \( h \) (reported in the figures) to be the \( h \)-period multiplier (although not rescaled by the long-run values of \( G_t \) and \( C_t \)). Panel A in Tables 1 and 2 reports the

\(^{10}\)CEX data may be subject to measurement error, especially income (Lusardi, 1996). This is the reason motivating the aggregate data analysis: to verify that CEX data gives qualitatively similar results to NIPA data at the aggregate level, although there are quantitative differences. The quantitative differences are more minor in the specification in differences, reported in the Not-for-Publication Appendix.

\(^{11}\)In particular, the differences between our Figure 1, Panel A and figure XII in Ramey (2011a) include: (i) a different sample, as Ramey’s (2011a) sample starts in 1947 while our starts in 1984, due to the lack of CEX data before 1984; (ii) a smaller number of variables included in the VAR; (iii) a different detrending specification. Figure 1 Panel B addresses the differences due to (iii); the Not-for-Publication Appendix investigates robustness to (i) and (ii).
peak multipliers for the various measures of aggregate consumption. Results in Table 1 are based on the VAR that does not include the deterministic trend components while those in Table 2 do. Panel A in the tables reports results for nondurable consumption in NIPA data, labeled "NIPA", while the row labeled "CEX, eq. (2)" reports the multiplier associated with aggregate consumption in CEX data. In all cases, the multipliers are negative and not statistically different (significance is evaluated by a bootstrap procedure where parameter estimation error is taken into account). We also report 68% confidence intervals.\textsuperscript{12} Overall, the responses are qualitatively very similar and their shapes are also very similar, which increases our confidence in using CEX consumption data in our analysis.

Let us elaborate on the size of the spending multipliers that we find, relative to those obtained in the literature. This is important, for several reasons. For example, during the recent financial crisis of 2007-2009, interest rates were stuck at the zero lower bound, which prevented the use of conventional monetary policy to mitigate the effects of the crisis and increased interest in understanding the effects of fiscal policy. It is also important in the light of the recent debate of the self-defeating effects of fiscal consolidation measures adopted by many advanced economies since 2010 (e.g. Gros, 2011).

Most of the literature focuses on output multipliers. For example, in her survey of the literature, Ramey (2011, p.683) notes that "it seems that the bulk of estimates imply that the aggregate multiplier for a temporary rise in government purchases not accompanied by an increase in current distortionary taxes is probably between 0.8 and 1.5". Similarly, Baunsgaard et al. (2012) note that output multipliers to a government spending shock range from 0 to 2.1, with a mean of 0.8 during the first year after the fiscal shock. In her own work in particular, Ramey (2011a, p. 30) finds that the elasticity of the GDP peak with respect to government spending (i.e. $max_{h}|\partial \ln GDP_t+h/\partial \ln G_t| \text{sign} \left( \frac{\partial \ln GDP_{t+h}}{\partial \ln G_t} \right) \right)$ is 0.23 and that the average ratio of nominal GDP to nominal government spending (i.e. $GDP/G$) was 4.9; thus, the peak multiplier is 1.1. However, the magnitude of the cumulative multiplier is sensitive to the sample size and the identification of the shock; for example, when focusing on the SPF shock on the period from 1983 onwards, Ramey finds a peak multiplier around

\textsuperscript{12}Note that we report 68% confidence intervals as they have been widely used in the literature on fiscal policy, so that we can compare our results with those in the existing literature.
It is important to note that we are studying the consumption multipliers, not output multipliers; thus, we cannot directly compare our results with the output multipliers discussed in the literature. Regarding the consumption multiplier, calculating it the same way and using the same sample as in Ramey (2011a), it equals $-0.36$; when we calculate the multiplier using exactly the same NIPA consumption data and model as in Ramey (2011a) but in our sub-sample we get a peak multiplier equal to $-0.55$ (see the Not-for-Publication Appendix). Thus, multipliers can vary a lot depending on the sample. The multipliers we find in our benchmark VAR with quadratic trend (reported in Table 2) is similar in magnitude to Ramey’s multiplier when calculated over our sub-sample, -0.81 for NIPA consumption data and -0.51 for CEX consumption aggregate data (and their confidence intervals includes both -0.55 and -0.36). So our conclusion is that the differences with the existing literature depend on the fact that the typical estimates for the multipliers are reported for output and, for the subset of papers that instead focus on consumption multipliers, the differences are due to different sample periods, as the size of the multiplier is unstable over time. In addition, not only multipliers may depend on the state of the economy and sample period, they may also depend on other variables. For example, Corsetti et al. (2009, 2010), Rossi and Zubairy (2011) and Davig and Leeper (2011) show that the effects of fiscal shocks may depend on the present and/or future path of monetary and/or fiscal policy, and whether the government plans to offset the shock with higher future taxes or lower future spending. In particular, Cimadomo et al. (2011) find that the economy’s reaction depends on whether

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13 Among recent contributions, Ilzetzki, Mendoza and Vegh (2013) find that the output multiplier differs depending on countries’ exchange rate regimes, openness to trade as well as income; in particular, the multiplier for high-income countries is higher than that in low-income countries. Brinca et al. (2014) study several countries and find that the size of the fiscal multiplier depends on the fraction of liquidity constrained individuals, providing additional support to our results. Nakamura and Steinsson (2014) calculate an output multiplier equal to 1.5.

14 The reason why the size of the multiplier is unstable over sub-sample might be due to the fact that the multiplier may vary depending on whether the economy is in an expansion or a downturn, as discussed in Auerbach and Gorodnichenko (2012), Baum et al. (2012) and Fazzari, Morley and Panovska (2014) for output multipliers, and different sub-samples may include mainly fiscal expansions or mainly fiscal contractions.
shocks are reversing or not (that is, whether they are associated with future expected public
spending growth below trend or above trend, respectively). In particular, Cimadomo et al.
(2011) include consumption multipliers in their analysis and show that shocks with reversals
have expansionary effects on output and consumption whereas shocks without reversal are
contractionary; they do not report multipliers, however, only impulse responses.

To summarize our results, we conclude that empirical results based on aggregate CEX
data are very similar to those currently reported in the literature, even in our sub-sample
and our simple VARs with fewer variables than in the literature (driven by the small sam-
ple constraints in CEX data). Thus, we can use CEX data in our analysis and focus on
small VAR without being too concerned about the potential misspecification induced by the
parsimonious number of variables that we consider. However, CEX data have an important
advantage relative to NIPA data: they can be disaggregated across individuals, and used to
evaluate the extent of heterogeneity in individual consumption responses to policy shocks.
The next two sections provide such analysis.

3 Our Approach

Our disaggregate analysis focuses on CEX data. The CEX is not really a genuine panel, where
the same individual is followed over time, but a rotating panel, where individuals remain in
the sample only for a limited number of quarters. Deaton (1985) discusses methodologies
for adapting the analysis of time series of cross section data to panels using pseudo-panels
identified by defining groups of individuals. For our main analysis, we construct a pseudo
panel dataset from the CEX by grouping households according to income, although we
explore grouping based on age as well. The challenge when picking the group definitions is
to not aggregate the individuals too much, otherwise we would not observe heterogeneity.
On the other hand, we cannot study individuals since each household is only in the survey
for four quarters. Thus, we choose group sizes that maintain the heterogeneity while keeping
enough households in each group. Income groups are based on income quintiles. Regarding
age, households fall into one of five possible groups, defined as: 15-24, 25-34, 35-44, 45-70,
and 71-90 year-old individuals. Sometimes, researchers drop students and retired households
to study consumption inequality over the workforce portion of the life cycle: see for instance Attanasio (1998) and Attanasio and Weber (1993). We do not follow this convention since our goal is to study differences in consumption responses across groups, where students and retirees could be potentially interesting groups. Table 3 contains the average cell size for each group category. In general, we have cell sizes similar to Attanasio and Weber (1993, 1995).\footnote{Note that the 45-70 age group contains more households, on average, than other age groups. While we could potentially split this group further, we are interested in this age group because it contains working-age individuals.}

In order to examine the consequences of a government spending policy shock, we consider a three variable VAR inspired by Ramey (2011a) and eq. (1), including the SPF fiscal shock, government spending, and consumption. As previously discussed, the VAR is identified with a recursive ordering procedure where the shock is ordered first and consumption last. We estimate the VAR separately for individuals belonging to each group \( j \), \( j = 1, \ldots, J \), where \( J \) is the total number of groups (\( J = 5 \) in our analysis). The household groups are identified based on the individual characteristics previously discussed (income and age). We also consider specifications that include or exclude a constant and a quadratic time trend. Specifically, our VAR is:

\[
A^j (L) Z^j_t = K^j + D^j_1 t + D^j_2 t^2 + U^j_t
\]

where \( Z^j_t \) is a vector containing the SPF shock, the log of real per capita government spending and the log of real per capita consumption for individuals belonging to group \( j \), \( A^j (L) = A^j_0 + A^j_1 L + \ldots + A^j_4 L^4 \), \( K^j, D^j_1, D^j_2 \) are vectors of parameters, and \( U^j_t \) is a vector of residuals. Again, in our benchmark results we let \( D_1 = D_2 = 0 \), although we investigate the robustness of the results to including a quadratic time trend in Section 6. Our choice of lag length is similar to Ramey (2011a). We estimate eq. (3) separately for each of the \( J \) groups of households.

The next two sections report estimated impulse responses (IRFs) to a positive government spending policy shock, as well as standard error bands calculated using a parametric bootstrap (Berkowitz and Kilian, 2000). The standard error bands have 68\% coverage rate,
as is common practice in the fiscal policy literature (see Ramey, 2011a).\textsuperscript{16} We also calculate peak responses that measure the effect of the policy shock and can be interpreted as a multiplier measure – see Spilimbergo et al. (2009) and Ramey (2011a)\textsuperscript{17} – and discuss results based on statistical tests on the pairwise differences between peak responses among the various groups.\textsuperscript{18}

\section{Heterogeneity in Individuals’ Responses to Government Spending Policy Shocks}

This section presents the main empirical results for the responses to a government spending shock. We focus our discussion on groups of individuals sorted by income levels, although we also briefly discuss results based on age groups.

To preview our results, in general we find substantial empirical evidence in favor of heterogeneity across consumers’ responses to an aggregate positive government spending policy shock. In particular, our main results show that the poorest and the oldest individuals’ consumption levels are the most positively affected by the shock. We also find that consumption of the working group as well as the wealthiest individuals is the most negatively affected by the government spending policy shock.\textsuperscript{19}

\textsuperscript{16}The confidence bands calculated via the bootstrap do not need to be symmetric (unlike those obtained by Monte Carlo simulations based on Normality).

\textsuperscript{17}Alternative multiplier measures include cumulative multipliers, constructed as the integral under the IRF of GDP associated with a peak response of government spending equal to one. Ramey (2011a) finds that the magnitude of the cumulative multiplier is sensitive to the sample size and the identification of the shock. For example, Ramey, 2011(a, p. 30) finds that, in the sample 1939 to 2008, the GDP peak multiplier is 1.1 and the cumulative multiplier is 1.2. When focusing on the SPF shock on the period from 1983 onwards, Ramey finds a peak GDP multiplier around 0.8 but a negative multiplier when the latter is constructed as the integral under the response function (Ramey, 2011a, p. 39). Thus, we focus on the peak multiplier in our analysis.

\textsuperscript{18}The significance is evaluated using a bootstrap procedure where parameter estimation error is taken into account.

\textsuperscript{19}Note that it is unlikely that our results are driven by a homogeneous response to a heterogeneous fiscal policy shock rather than being heterogeneous responses to a homogeneous fiscal policy shock (as we argue)
Impulse responses for consumption of individuals grouped by income quintiles are displayed in Figure 3. It is noteworthy that the richest quintiles are hurt the most in terms of consumption by the increase in government spending, while consumption of the poorest increases instead. Table 1, Panel B, reports peak multipliers. The multipliers are negative for the richest groups and positive for the poorest groups, increasing almost monotonically across groups. We test the statistical significance of the differences among multipliers across groups using the bootstrap, which, by construction, takes into account parameter estimation error. Interestingly, the richest group is statistically significantly different from the fourth and fifth poorest quantiles, while the second group is statistically significantly different from the fourth. Thus, clearly, the poorest quintile’s responses are statistically significantly different from those of the richest groups. These results point to the existence of substantial heterogeneity in the responses to government spending shocks of consumers that differ by income.

Our results have important implications for the existing debate of the effects of government spending shocks – see Engemann, Owyang and Zubairy (2008) for a survey of the debate. In fact, theoretical models have very different implications regarding the effects of government spending shocks on consumption. According to standard RBC models, consumption should decrease after a permanent positive government spending shock, whereas consumption should increase in the textbook IS-LM model. In fact, according to the standard RBC model, households anticipate the higher taxes that are necessary to repay the (non-productive) government spending, which lowers the net present value of after tax income, and thus would be affected by a negative wealth effect. Therefore, they react to the increase in government spending by lowering their consumption and their leisure. On the other hand, in the IS-LM model, consumers behave in a non-Ricardian fashion and real disposable income is the most important variable affecting consumption. This is because individuals’ consumption is a function of their current income and not of their life-time resources. For example, in the presence of credit constraints, we should observe that the increase in government spending causes consumption to increase. Gali et al. (2007) show since CEX is a random sample and since the fiscal shock measure we use is an aggregate measure.
that a New Keynesian model where a fraction of households consume all their income in every period can explain how consumption increases after a government spending shock.\textsuperscript{20} In our analysis, we are able to disentangle the consequences of government spending shocks on consumers with different levels of income, and therefore, facing different levels of credit constraints.\textsuperscript{21} Consumers in the poorest income quantiles, which are more likely to be credit constrained, end up increasing consumption. On the other hand, consumers in the richest income quantiles, which are less likely to be credit constrained, end up decreasing consumption, as the theory predicts.

The reason why we can claim that poorest individuals are more likely to be credit constrained is the empirical evidence discussed in Attanasio et al. (2008), according to which low income consumers are substantially more credit constrained than high income consumers. Interestingly, we find that approximately 20\% of consumers (the wealthiest) increase their consumption after a government spending shock, and hence are estimated not to be credit constrained. This estimate is very similar to that reported in Attanasio et al. (2008) for CEX data, according to which approximately 15\% of the population with the highest income is not liquidity constrained.\textsuperscript{22}

Finally, note that, typically, the richest individuals would have higher consumption levels than poorer individuals.\textsuperscript{23} Fiscal shocks, by increasing consumption of the poorest and decreasing consumption of the richest, overall tend to decrease consumption heterogeneity.

We also investigate responses based on age groups. Figure 4 shows the impulse response of consumption to a positive government spending shock for individuals grouped by age. The

\textsuperscript{20}Gali et al. (2007) show that another necessary condition for consumption to rise in response to a fiscal expansion is price stickiness in goods markets as well as, in one version of their model, imperfectly competitive labor markets.

\textsuperscript{21}While income may not necessarily reflect the degree of liquidity constraints faced by an individual, in the next paragraph we discuss the empirical evidence that supports the interpretation that individuals with low income levels may face liquidity constraints.

\textsuperscript{22}In their paper, Attanasio et al. (2008) identify consumers as being credit constrained if they are responsive to interest rates and loan maturity changes, since a longer debt maturity decreases the size of the monthly payment and allows consumers to sign up for a larger debt.

\textsuperscript{23}We report summary statistics on CEX data in the Not-for-Publication Appendix; the summary statistics confirm this fact.
age groups that are most negatively, persistently and significantly affected by the fiscal shock are the third and fourth quintiles, which correspond to people aged 35 to 70, who are possibly in wealthiest period of their lives. The oldest category, instead, has a significantly positive increase in consumption on impact; we conjecture that individuals start to decumulate their wealth when retiring, and might behave more like hand-to-mouth consumers. Panel B in Tables 1 and 2 provide additional results by reporting the peak multiplier of consumption for each group. The middle age groups have the most negative peak multiplier.\footnote{The multipliers are in unit terms. That is, a dollar increase in government spending leads to an increase in consumption equal to the value of the multiplier.} The oldest category has a positive peak response.\footnote{Note that these results seem at odd with the finding in Attanasio et al. (2008) that there is no evidence that the younger groups are more credit constrained that the older groups. However, note that their oldest group includes individuals that are 55 year-old or older. If we group together individuals that are 45 to 70 year-old and individuals that are 71 or older, we also do not find empirical evidence that consumption increases.} Note that the youngest group has a negative impact response, but the peak multiplier is positive as the largest response in magnitude occurs after two periods and it is positive. Overall, these results provide empirical evidence that age may also matter in the response to a government spending shock.

5 Aggregate Responses

An additional benefit of using household level data besides analyzing heterogeneity is that we can control the aggregation process. This enables us to avoid the aggregation bias that might be present when working with aggregate data. Specifically, Attanasio and Weber (1993, 1995) point out that an aggregation bias will be introduced if researchers use aggregate data by taking the logarithm of the mean (the common procedure used when working with aggregate data) instead of the mean of the logarithm. In order to construct our aggregate pseudo panel dataset we calculate:

$$
\frac{1}{H_t} \sum_{i=1}^{H_t} \ln(c_{i,t}),
$$

(4)
where $c_{i,t}$ represents individual $i$’s consumption level, $H_t$ is the total number of households at time $t$, and $t$ is time. When only aggregate data is available, one would instead calculate:

$$\ln \left( \frac{1}{H_t} \sum_{i=1}^{H_t} c_i \right).$$  \hspace{1cm} (5)

Note that the latter is the measure we discussed in Section 2. By comparing (4) and (5) we can compare average multipliers calculated across individual responses with the multiplier based on aggregate consumption data. Note that neither eq. (4) nor equation (5) are a better measure of consumption than the other: which is best depends on the scope of the analysis. Eq. (5) is useful to understand how (log) consumption responds on average (across individuals) to a shock; however, this does not necessarily provide a measure of how the average individual (log) consumption responds to the shock, which is instead what eq. (4) reports.

Figures 1 and 2 compare impulse responses using aggregate CEX consumption data (eq. (4), depicted in Panel C) and the CEX with aggregate data only (eq. (5), depicted in Panel B). Figure 1 refers to the model without trend while Figure 2 refers to the model with quadratic trend. The figures shows that the responses of aggregate CEX consumption, eqs. (4) or (5), are quite different from each other. The response of aggregate consumption calculated according to eq. (4) are much smaller in magnitude and tend to become positive after a few quarters. The response of aggregate consumption calculated according to eq. (5) are instead negative on impact, reaching their peak after about a year, and remain negative for several quarters. The latter are much more similar to the pattern found in NIPA data by Ramey (2011a), among others. The implication is that by using aggregate data that do not control for the aggregation bias, researchers might overestimate the negative effects of government spending shocks.

6 Robustness Analyses

In this section, we show that our empirical results are robust to considering different detrending procedures, and to enlarging the VAR to include more variables.
First, we consider the following specification: we estimate eq. (3) with the deterministic and quadratic trend. The identification strategy and other details are the same as in Section 3. Figure 5 reports responses for the government spending shock for individuals sorted by income group. The responses are very similar to those reported in Section 3 and convey the same message: the richest quintile responds negatively on impact, then the responses monotonically change across income quintiles until they become positive for the two poorest income quintiles. Responses for individuals sorted by age group (Figure 6) show less differences than those sorted by income, although the response of the youngest quintiles are mostly negative on impact and those of the oldest quintile are positive. The Not-for-Publication Appendix also shows that our results are robust to estimating the VAR using consumption in first differences.

Finally, we consider enlarging the VAR information set to investigate the effects of distortions deriving from the limited number of variables in the VAR. We consider the same specification as in Ramey (2011a), which includes the government spending shock, government spending, income, the Treasury bill rate, the average marginal income tax and consumption, in this order. In this case, we estimate the VAR with two lags in order to prevent excessive parameter proliferation. We report results based on the VAR without trend; the Not-for-Publication Appendix shows that the results are robust to including a quadratic trend. Figure 7 shows that our results are robust for both individuals sorted by income (Panel A) and by age (Panel B).

7 Conclusion

Our empirical results uncover significant differences in disaggregate individuals’ consumption responses to government spending shocks, which would not be possible to uncover with traditional analyses based on aggregate data.

In particular, unexpected increases in government spending policy hurt the working-age and the wealthiest individual the most in terms of consumption. The wealthiest experience the highest cumulative drop in consumption whereas consumption of the poorest categories increases significantly. Thus, government spending policy shocks tend to decrease consump-
tion inequality.

Another advantage of using disaggregate data is that it is possible to create aggregate data that are more suitable for economic analyses. We find that responses on aggregated CEX data based on disaggregated data behave differently from traditional aggregate data responses to a government spending shock. In particular, traditionally aggregated CEX data show a delayed and significant decrease in aggregate consumption after a government spending shock, which instead tends to be smaller or even positive according to our aggregate CEX measure.

These results suggest that it is important to allow for heterogeneity in individuals’ behavior when studying the effects of fiscal policy shocks. Existing theoretical models suggest that fiscal shocks may have very different effects on consumption depending on whether consumers are credit constrained. Our empirical results show that indeed individuals respond to shocks differently depending on their wealth; this finding highlights the fact that, indeed, consumers who are most likely credit constrained do increase their consumption after an unexpected increase in government spending. As we show, these interesting results are in line with theoretical macroeconomic models that allow for a fraction of consumers to be credit constrained.

Note that our results depend on the VAR specification and choice of variables we make. Considering VARs with a large number of variables is beyond the scope of our paper. In a recent paper, De Giorgi and Gambetti (2012) consider factor models to extract information on the state of the macroeconomy. It could be interesting to consider large dimensional VARs, although we leave it for future research. Another interesting extension would be to study how multipliers depend on the components of government spending. Such a study has been done for US output multipliers by Auerbach and Gorodnichenko (2012). They found that the effects of a government spending shock on output depend on the components of government spending; we conjecture that a similar result may hold for consumption multipliers. We also leave this analysis for future research.

\footnote{As noted by a referee, Forni and Gambetti (2011) provide tests for informational sufficiency for VARs that could be used in this context.}
8 References


9 Tables and Figures

<table>
<thead>
<tr>
<th>Table 1. Multipliers in Benchmark VAR Without Trend</th>
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<tbody>
<tr>
<td>Panel A. Aggregate Consumption</td>
</tr>
<tr>
<td>Peak IRF   68% C.I.</td>
</tr>
<tr>
<td>NIPA       -1.08 (-1.62; -0.45)</td>
</tr>
<tr>
<td>CEX, eq. (2) -1.05 (-2.07; -0.66)</td>
</tr>
<tr>
<td>Panel B.  Income Groups Age Groups</td>
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<tr>
<td>Peak IRF   68% C.I. Peak IRF 68% C.I.</td>
</tr>
<tr>
<td>1&lt;sup&gt;st&lt;/sup&gt; Quintile -1.71 (-2.79; -1.15) 1.39 (-2.83; 3.02)</td>
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<tr>
<td>2&lt;sup&gt;nd&lt;/sup&gt; Quintile -1.09 (-2.11; -0.46) -1.07 (-2.15; 1.14)</td>
</tr>
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<td>3&lt;sup&gt;rd&lt;/sup&gt; Quintile -1.17 (-2.17; 1.13) -1.03 (-2.25; -0.80)</td>
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<tr>
<td>4&lt;sup&gt;th&lt;/sup&gt; Quintile 0.87 (-1.04; 1.98) -0.73 (-1.66; -0.45)</td>
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<td>5&lt;sup&gt;th&lt;/sup&gt; Quintile 1.17 (-1.35; 2.48) 1.32 (-1.85; 2.52)</td>
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<tr>
<td>Panel C.  Peak IRF 68% C.I.</td>
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<tr>
<td>CEX, eq. (4) -0.40 (-1.49; 1.04)</td>
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<td></td>
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<tr>
<td>----------------</td>
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<tr>
<td></td>
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<tr>
<td>NIPA Cons.</td>
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<tr>
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<th>Age Groups</th>
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<td>68% C.I.</td>
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<tr>
<td>1&lt;sup&gt;st&lt;/sup&gt; Quintile</td>
<td>-1.09</td>
<td>(-1.99; 0.67)</td>
</tr>
<tr>
<td>2&lt;sup&gt;nd&lt;/sup&gt; Quintile</td>
<td>-0.64</td>
<td>(-1.42; 1.11)</td>
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<tr>
<td>3&lt;sup&gt;rd&lt;/sup&gt; Quintile</td>
<td>0.80</td>
<td>(-1.19; 1.80)</td>
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<tr>
<td>4&lt;sup&gt;th&lt;/sup&gt; Quintile</td>
<td>0.88</td>
<td>(-0.86; 1.86)</td>
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<td>5&lt;sup&gt;th&lt;/sup&gt; Quintile</td>
<td>1.73</td>
<td>(-1.21; 2.85)</td>
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### Table 3. Average Cell Size by Groups

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<th>25-34</th>
<th>35-44</th>
<th>45-70</th>
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<table>
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<tr>
<th>Income Groups</th>
<th>80-100%</th>
<th>60-79%</th>
<th>40-59%</th>
<th>20-39%</th>
<th>0-19%</th>
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<tbody>
<tr>
<td>Cell Size</td>
<td>268.91</td>
<td>434.45</td>
<td>474.84</td>
<td>495.11</td>
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### Table 4. Multipliers in Large Dimensional VAR Without Trend

#### Panel A. Aggregate

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</tr>
</thead>
<tbody>
<tr>
<td>NIPA Cons.</td>
<td>-0.27</td>
<td>(-0.51; -0.12)</td>
</tr>
<tr>
<td>CEX, eq. (2)</td>
<td>-0.47</td>
<td>(-1.15; 0.57)</td>
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#### Panel B. Income Groups Age Groups

<table>
<thead>
<tr>
<th></th>
<th>Peak IRF</th>
<th>68% C.I.</th>
<th>Peak IRF</th>
<th>68% C.I.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1&lt;sup&gt;st&lt;/sup&gt; Quintile</td>
<td>-1.11</td>
<td>(-1.99; -0.71)</td>
<td>-1.51</td>
<td>(-2.98; 1.89)</td>
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<tr>
<td>2&lt;sup&gt;nd&lt;/sup&gt; Quintile</td>
<td>-0.42</td>
<td>(-1.30; 0.53)</td>
<td>-0.90</td>
<td>(-1.70; 1.04)</td>
</tr>
<tr>
<td>3&lt;sup&gt;rd&lt;/sup&gt; Quintile</td>
<td>-0.75</td>
<td>(-1.36; 1.24)</td>
<td>-0.36</td>
<td>(-1.37; 0.56)</td>
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<tr>
<td>4&lt;sup&gt;th&lt;/sup&gt; Quintile</td>
<td>-0.39</td>
<td>(-1.22; 1.04)</td>
<td>-0.34</td>
<td>(-0.93; 0.35)</td>
</tr>
<tr>
<td>5&lt;sup&gt;th&lt;/sup&gt; Quintile</td>
<td>-0.28</td>
<td>(-1.32; 1.38)</td>
<td>0.95</td>
<td>(-1.66; 1.93)</td>
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#### Panel C.

<table>
<thead>
<tr>
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</tr>
</thead>
<tbody>
<tr>
<td>CEX, eq. (4)</td>
<td>-0.27</td>
<td>(-1.05; 0.65)</td>
</tr>
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</table>

Notes to the Tables. Notes to Tables 1, 2 and 4: The table reports the peak multiplier of nondurable consumption to a government spending policy shock in aggregate NIPA and CEX data using eq. (2) (Panel A) as well as for individuals (Panel B) sorted according to their income (columns labeled "Income Groups") and age (columns labeled "Age Groups"). It also reports 68% confidence bands. The multipliers for aggregate CEX nondurable consumption calculated according to eq. (4) are listed in Panel C.

Notes to Table 3: This table reports the average cell size for each group category where the cell size is how many households are used to make one quarterly observation.
Figure 1. Impulse-Responses in Aggregate Consumption Data.

VAR without Deterministic Trend.

Panel A. NIPA Consumption

Panel B. CEX Aggregate, eq. (5)

Panel C. CEX Aggregate, eq. (4)

Notes to the Figure. The figure reports the response of aggregate nondurable consumption in NIPA data (Panel A) as well as in CEX data (Panels B-C). The VAR is estimated without a deterministic nor quadratic time trend.
Figure 2. Impulse-Responses in Aggregate Consumption Data.

VAR with Quadratic Time Trend.

Panel A. NIPA Consumption

Panel B. CEX Aggregate, eq. (5)

Panel C. CEX Aggregate, eq. (4)

Notes to the Figure. The figure reports the response of aggregate nondurable consumption in NIPA data (Panel A) as well as in CEX data (Panels B-C). The VAR is estimated with a quadratic time trend.
Figure 3. Impulse Responses of Nondurable Consumption by Income Group (68% standard error bands)

Notes to the Figure. The figure reports the response of nondurable consumption for various income groups in CEX data with 68% confidence bands. The richest group is depicted in the top left panel, labeled "First Quintile"; the second richest group is depicted in the top middle panel, labeled "Second Quintile"; and so forth, until the poorest group, depicted in the bottom right panel, labeled "Fifth Quintile". The VAR is estimated without a deterministic nor quadratic time trend.
Figure 4. Impulse Responses of Nondurable Consumption by Age Group (68% standard error bands)

Notes to the Figure. The figure reports the response of nondurable consumption for various age groups in CEX data with 68% confidence bands. The youngest group is depicted in the top left panel, labeled "First Quintile"; the second youngest group is depicted in the top middle panel, labeled "Second Quintile"; and so forth, until the oldest group, depicted in the bottom right panel, labeled "Fifth Quintile". The VAR is estimated without a deterministic nor quadratic time trend.
Figure 5. Impulse Responses of Nondurable Consumption by Income Group (68% standard error bands)

Notes to the Figure. The figure reports the response of nondurable consumption for various income groups in CEX data with 68% confidence bands. The richest group is depicted in the top left panel, labeled "First Quintile"; the second richest group is depicted in the top middle panel, labeled "Second Quintile"; and so forth, until the poorest group, depicted in the bottom right panel, labeled "Fifth Quintile". The VAR is estimated with a quadratic time trend.
Figure 6. Impulse Responses of Nondurable Consumption by Age Group (68% standard error bands)

Notes to the Figure. The figure reports the response of nondurable consumption for various age groups in CEX data with 68% confidence bands. The youngest group is depicted in the top left panel, labeled "First Quintile"; the second youngest group is depicted in the top middle panel, labeled "Second Quintile"; and so forth, until the oldest group, depicted in the bottom right panel, labeled "Fifth Quintile". The VAR is estimated with a quadratic time trend.
Notes to the Figure. The figure reports the response of nondurable consumption for various income groups in CEX data with 68% confidence bands. The richest group is depicted in the top left panel, labeled "First Quintile"; the second richest group is depicted in the top middle panel, labeled "Second Quintile"; and so forth, until the poorest group, depicted in the bottom right panel, labeled "Fifth Quintile". The VAR includes the shock, government spending, income, interest rates, the tax rate and consumption. The VAR is estimated without a deterministic nor quadratic time trend.
Figure 7b. Impulse Responses of Nondurable Consumption by Age Group in a Larger VAR without Trend

Notes to the Figure. The figure reports the response of nondurable consumption for various age groups in CEX data with 68% confidence bands. The youngest group is depicted in the top left panel, labeled "First Quintile"; the second youngest group is depicted in the top middle panel, labeled "Second Quintile"; and so forth, until the oldest group, depicted in the bottom right panel, labeled "Fifth Quintile". The VAR includes the shock, government spending, income, interest rates, the tax rate and consumption. The VAR is estimated without a deterministic nor quadratic time trend.