The Aging of the Baby Boomers: Demographics and Propagation of Tax Shocks*

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Abstract

We study the consequences of population aging for the response of the aggregate labor market to income tax cuts in the United States over the post-World War II period. Using narratively identified tax changes as proxies for structural shocks, we establish that the responsiveness of unemployment rates to tax changes largely varies across age groups: the unemployment rate response of the young is nearly twice as large as that of the old. This heterogeneity is the channel through which shifts in the age composition of the labor force impact the response of the aggregate unemployment rate to tax cuts. We find that the aging of the baby boomers considerably reduces the effects of tax cuts on aggregate unemployment.

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1 Introduction

The post-World War II baby boom and the subsequent aging of the baby boomers resulted in dramatic shifts in the age composition of the labor force in the United States. In this paper, we investigate the consequences of such demographic change for the propagation of tax cuts in the U.S. labor market. Specifically, we quantify how shifts in the age composition of the labor force affect the response of the aggregate unemployment rate to unanticipated tax cuts. We argue that the age composition of the labor force constitutes a quantitatively important channel for the transmission of tax shocks to aggregate unemployment.

The first contribution of the paper is to document that the unemployment responsiveness to tax shocks largely varies across age groups: the unemployment rate response of the young is nearly twice as large as that of the old. This heterogeneity is the channel through which shifts in the age composition of the labor force affect the response of the aggregate unemployment rate to tax changes. The second contribution is to quantify the impact of an aging labor force on the propagation of tax shocks. We quantify that the aging of the baby boomers reduces the effects of tax cuts on aggregate unemployment by 40 percent.

The debate in the aftermath of the Great Recession of 2007 has led to renewed interest in the question of how fiscal policy affects macro aggregates. Not surprisingly, a growing strand of the empirical literature investigates the effects of government purchases and taxes (see Romer and Romer, 2010; Barro and Redlick, 2011; Ramey, 2011; Mertens and Ravn, 2013; Mertens and Montiel-Olea, 2018).[1] This literature has considered aggregate macroeconomic variables, which is the natural starting point for analyzing the economic forces that shape the aggregate response to fiscal shocks. Here, we pursue a disaggregated analysis by considering one specific dimension of heterogeneity, age. This approach sheds light on the link between microeconomic behavior and macroeconomic effects of tax changes. We emphasize, however, that our ultimate goal is to gauge the implications of demographic change for the *aggregate* labor-market response to tax changes. To date, this paper is the first attempt to tackle this question.[2]

Recent work has also studied the implications of demographic change for macroeconomic

[1] See Ramey and Shapiro (1998), House and Shapiro (2006, 2008), Pappa (2009), Brückner and Pappa (2012), Auerbach and Gorodnichenko (2012), Favero and Giavazzi (2012), Cloyne (2013), Ramey and Zubairy (2018), Nakamura and Steinsson (2014), Acconcia et al. (2014), Mertens and Ravn (2014), and Caldara and Kamps (2017) for further references.

[2] Anderson et al. (2016) document heterogeneous effects of government spending shocks on consumption, depending on income and age.

analysis. For instance, Shimer (1999) shows that the entry of the baby boomers into the labor force in the late-1970s, and their aging, accounts for most of the low-frequency movements in the U.S. unemployment rate since World War II. Jaimovich and Siu (2009) show that such demographic change accounts for a significant fraction of the decrease in business cycle volatility observed in the United States since the mid-1980s. In this paper, we argue that the aging of the baby boomers considerably reduces the effects of tax changes on aggregate unemployment.

Furthermore, we argue that assessing the effects of tax changes across different age groups is also relevant for distinguishing between competing transmission channels of tax shocks at work in the U.S. labor market. Understanding if and the extent to which young, prime-age and old workers in the labor force display differences in the unemployment responsiveness to aggregate tax shocks would seem important for understanding why aggregate unemployment responds to tax cuts as much as it does. Analogously, Ríos-Rull (1996), Gomme et al. (2005), Hansen and İmrohoroğlu (2009), and Jaimovich et al. (2013) assess the aggregate implications of age-specific differences in cyclical movements of hours worked.

To estimate the responses of age-specific unemployment rates to tax changes, we rely on narrative identification of tax shocks (see Romer and Romer, 2009, 2010). Specifically, we use narratively identified tax changes as proxies for structural tax shocks, and structural vector autoregressions ("proxy SVAR") to estimate the dynamic responses to a tax cut (see Mertens and Ravn, 2013; Mertens and Montiel-Olea, 2018). Using Current Population Survey (CPS) data, we construct average marginal income tax rates (AMTR) by age groups, as we are interested in the transmission mechanism of tax changes that operates through incentive effects on intertemporal substitution. In addition, we build a new set of age-specific proxies to account for the fact that historically tax reforms may have changed AMTR of different age groups differently. Indeed, our measurement points to substantial age heterogeneity in AMTR and how tax reforms impacted AMTR of different age groups. Proxy SVAR are estimated separately for the young (16-34 years old), prime-age (35-54 years old), and old (55 years and older), using our constructed age-specific proxies as external instruments for age-specific AMTR.

We establish that the responses of the unemployment rates to tax changes largely varies across age groups: the unemployment rate response of the young is nearly twice as large as that of the old. By contrast, we show that the age-specific labor force shares are in fact unresponsive to the (narratively identified) changes in AMTR. This empirical finding is, perhaps, not surprising as the observed demographic trends in the age composition of the labor force in the United States are largely determined by fertility decisions made long before a specific tax shock. Thus, the age composition of the labor force is largely predetermined at the time of a legislated tax change. In addition, the post-war baby boom and the aging of the baby boomers in the last thirty years resulted in large movements in the age composition of the labor force. As a result, time-series variation in labor force shares by age abounds.

We use these two pieces of evidence to measure by how much the responsiveness of the aggregate U.S. unemployment rate to tax changes depends on the age composition of the labor force. Specifically, we construct an aggregate unemployment response to tax shocks, that accounts for the observed movements in the age composition of the labor force. The implied response provides a simple quantitative accounting of how the observed demographic trends in the United States impact the effectiveness of tax cuts in reducing aggregate unemployment. When an economy is characterized by a smaller share of young workers, everything else equal, one observes a smaller aggregate response to tax cuts. We find that the aging of the baby boomers reduces the response of the aggregate unemployment rate to tax cuts by 40 percent.

The implications for fiscal policy are far-reaching. In the United States, given the current fertility and mortality rates, the working-age population is expected to become older. Similar estimates and projections apply to Japan and most industrialized countries in Europe. The results in this paper indicate that tax shocks of the size observed in the United States since World War II are becoming increasingly less effective in stimulating economic activity.

2 Basic Facts on Population Aging

In this section we provide a bird's eye view of the aging of the workforce observed in the United States in the last thirty years. The post-WWII baby boom and the subsequent baby bust resulted in dramatic shifts in the age composition of the working-age population, labor force, and the pool of employment and unemployment (see Figure 1, and B.1, B.2 and B.3 in Appendix B). To the extent that young, prime-age, and old feature different labor force attachment, turnover rates, and job search intensities, population aging has important implications for the aggregate labor market response to tax changes. These observations motivate our paper.

Working-age population Panels A and B in Figure 1 report the average age and the shares by age of the U.S. working-age population, respectively. Two patterns emerge. First, population has been aging since the mid-1980s. Second, the average age of the population declined over the course of twenty-five years from the early-1960s to the mid-1980s as a result of the sharp increase in birth rates after World War II. This is the so-called “baby boom.” In the early-1960s, birth rates started to decline towards levels prior to the baby boom, which led to the subsequent baby bust. Since the late-1980s, population has been aging fueled by the aging of the baby boomers.

These slow-moving trends resulted in large shifts in the age composition of the population. The share of the 20-34 years old increased by 10 percentage points (from approximately 35 to 45 percent) over twenty years from 1960 to 1980. By contrast, during the same period, the population share of the 35-54 years old declined by nearly the same amount. The population share of the 55-64 years old remained approximately constant over the same period. It starts declining in the early-1980s to reach a trough in the mid-1990s. At that time, it sharply reverts to steady growth, reaching roughly 22 percent of the overall population in 2015. The share of the 20-34 years old in the working-age population starts its decline in the mid-1980s, reaching a plateau in the early-2000s.

Labor force (employment plus unemployment) The demographic trends observed in the working-age population have led to changes in the age composition and so the average age of the labor force. Notably, the labor force (see Figure B.1), as the working-age population, has been aging since the mid-1980s. The share of the 20-34 years old in the labor force raised by more than 10 percentage points (from approximately 35 to 48 percent) over fifteen years from the mid-1960s to early-1980s. During the same period, the share of the 35-54 years old declined by approximately 10 percentage points, whereas the labor force share of the 55-64 years old starts declining in the early-1970, reaches a trough of 10 percent in the mid-1990s, and it has been steadily increasing since then.

The average age of the employed (see Figure B.2) tracks closely that of the labor force. This observation is not surprising as employment represents nearly 95 percent of the labor force for 1950-2015. Movements in the average age of the unemployed, and shifts in their unemployment shares, are substantially larger than those in employment (see Figure B.3). In the mid-1950s, the average age of an unemployed worker was 39 years, whereas, in the 1980s, the average age was as low as 33. Yet, as of 2015, an unemployed is, on average, of nearly the same age as of an unemployed in the years preceding the baby boom. The unemployment share of the 20-34 years old raised by nearly 20 percentage points (from approximately 45 to 65 percent) from the mid-1960s to the 1980s. Since 1980, the share of the 20-34 years old has been declining at a nearly constant pace. As of 2015, they represent 49 percent of the unemployment pool. During the same period, the unemployment share of the 35-54 years old has instead declined and then raised, as a mirror image of the unemployment share of the 20-34 years old. Finally, the unemployment share of the 55-64 years old declined from the mid-1950s to the 1990s, and it has been steadily raising since then. As of 2015, they constitute 14 percent of unemployed persons.

3 Marginal Tax Rates by Age

In this section we describe the methodology to construct average marginal tax rates (AMTR) by age groups. Based on Barro and Redlick (2011), and most of the literature thereafter, we consider a notion of labor income that includes wages, self-employment, partnership, and S-corporation income. Data are taken from the CPS March Supplement that allows us to match individual income and demographic characteristics, such as age. AMTR is the sum of the federal individual income tax and the payroll (FICA) tax. We use NBER-TAXSIM to simulate marginal individual income tax rates and marginal payroll tax rates at the individual level. We then construct AMTR by age groups as the sum of average marginal individual income tax rates (AMIITR) and average marginal payroll tax rates (AMPTR), using adjusted gross income shares as weights. As such, we compute an hitherto unexplored measured of AMTR conditioning on the age composition of taxpayers. (We refer the reader to Appendix A.1 for more details about the construction of the AMTR series.)

Figure 2 reports aggregate and age-specific AMTR for the sample period 1961-2012.[3] Three patterns emerge. First, aggregate AMTR display a marked upward trend from the early-1960s to the early-1980s. It fluctuates in the 24-27 percent range over roughly ten years from 1961 to 1970. In the 1970s, AMTR sharply rise from 25 percent towards the post-war peak of 38 percent in the early-1980s. This acceleration was primarily due to the bracket creep effects induced by rising inflation over the so-called Great Inflation of the 1970s. After the 1980s, the sustained rises in the FICA tax have been almost entirely offset by reductions in the federal individual income tax rates, which have remained in the 20-25 percent range since then. In addition to these long-run trends, the time series of AMTR features substantial year-to-year variation with a standard deviation of 4.1 percent. As discussed in Mertens and Montiel-Olea (2018), the bulk of this year-to-year variation is driven by statutory changes in federal individual income taxes. Consistent with the literature, AMTRs do not include

[3]Our sample is constrained by CPS data as its availability starts in 1961.

state-level taxes. However, the amount of short-run variation in state-level marginal tax rates is small (see Barro and Redlick, 2011).

Second, AMTR differ by age, even though less than one would have expected a priori. The exception is the age group 16-24 with AMTR that are considerably below the aggregate; their average AMTR is 28 percent compared with the aggregate AMTR of 30.3 percent. The average AMTR is 30.1 percent for the group 25-34 and 30.8 percent for the groups 35-44 and 55-64. Third, the dynamics of the tax rates are remarkably similar across the different age groups, tracking closely the aggregate AMTR, with the lowest correlation being 0.93.

4 Econometric Methodology

In this section we discuss the identification of tax shocks, specification, and estimation.

4.1 Identification

We use structural vector autoregressions (SVAR) to measure the dynamic effects of changes in AMTR. SVAR have been extensively used in macroeconomics to evaluate the effects of fiscal policy actions as well as other aggregate shocks, such as monetary policy, technology, and oil price shocks. (See Ramey (2016) for a survey of the literature.) As in the SVAR tradition, we associate a "tax shock" to a VAR innovation to the AMTR that jointly satisfies three criteria: (i) it is unpredictable, given current and past information; (ii) it is uncorrelated with other structural shocks; and (iii) it is unanticipated, that is, it is not news about future policy actions.

As shown by Figure 2, the post-WWII history of U.S. federal income tax policy includes several large increases and decreases in marginal tax rates, which arguably provides valuable identifying variation. Yet, the vast majority of the observed legislated changes in tax rates result from policy actions aimed at offsetting cyclical downturns. This poses well-known challenges for the identification of the causal effects of tax changes on aggregate outcomes.

To address this issue, identification of tax shocks is obtained by SVAR and proxies for exogenous variation in tax rates as external instruments (see Mertens and Ravn, 2013). To this goal, we construct time series of age-specific proxies for exogenous changes in age-specific AMTR. Our strategy follows Mertens and Montiel-Olea (2018). To select instances of exogenous variation in tax rates, they rely on the narrative approach of Romer and Romer (2009): changes in total tax liabilities are classified as "exogenous" based on the motivation for the legislative action being either long-run considerations that are unrelated to the business cycle or inherited budget deficits. An additional concern is that legislated tax changes are often implemented with a considerable lag, which can generate anticipation effects. Indeed, Mertens and Ravn (2012) provide evidence of aggregate effects of legislated tax changes prior to their implementation. To avoid these anticipation effects, we consider observations on individual income tax liability changes legislated and implemented within the year as in Mertens and Ravn (2013). Based on these considerations, Mertens and Montiel-Olea (2018) identify seven exogenous tax reforms.

In Table 1, we report how each of these tax reforms changed age-specific AMTR. Specifically, the impact of a reform is measured as the difference between two counterfactual tax rates. The first counterfactual tax rate is calculated using the year $t-1$ income distribution and year t statutory tax rates and brackets. The second counterfactual tax rate is calculated based on the year $t-1$ income distribution and year $t-1$ statutory tax rates and brackets. The difference between the two isolates then the impact that a tax reform implemented in year t had on the AMTR. An issue that arises in this type of calculations is the indexing of the federal tax system starting in 1985.[4] To address this concern, we rescale incomes by the automatic adjustments in bracket widths embedded in the federal tax code.

Table 1 reveals that tax reforms had a similar impact on AMTR across all age groups. The sign of the changes in AMTR induced by the selected tax reforms is the same for all age groups, such that, say, a tax cut in the aggregate AMTR is indeed a tax cut for individuals of all ages. But the magnitude of these changes varies by age, with the 16-24 and 65+ age groups usually experiencing smaller changes.

4.2 Specification and estimation

First introduced by Sims (1980), SVAR have been widely used to study the joint dynamic behavior of multiple aggregate time series by allowing for general feedback mechanisms. Specifically, SVAR first isolate unpredictable variation in policy and outcome variables and then sort out the contemporaneous causal relationships by imposing identifying restrictions. Since the system allows for all possible dynamic causal effects, any linear (or linearized) dynamic stochastic general equilibrium (DSGE) model can be expressed in a state space form that yields a VAR representation for observables that are available to the econometrician (see Fernández-Villaverde et al., 2007). In addition, SVAR also identify the expected future

[4] The Economic Recovery Tax Act (ERTA) of 1981 ruled for automatically increasing personal exemptions, standard deductions, and bracket widths by the percentage change in the CPI starting in 1985.

path of policy variables. This is important for interpreting the estimates as expectations about the persistence of policy actions are arguably key drivers of the economy's response to discretionary tax changes.

Specification The baseline reduced-form VAR specification is

$$\begin{bmatrix} \text{AMTR}_t \\ \text{URATE}_t \\ \text{PRATE}_t \\ \mathbf{X}_t \end{bmatrix} = d + A(L) \begin{bmatrix} \text{AMTR}_{t-1} \\ \text{URATE}_{t-1} \\ \text{PRATE}_{t-1} \\ \mathbf{X}_{t-1} \end{bmatrix} + \begin{bmatrix} e_t^{\text{AMTR}} \\ e_t^{\text{URATE}} \\ e_t^{\text{PRATE}} \\ e_t^{\mathbf{X}} \end{bmatrix}, \tag{1}$$

where d is a constant and $A(L)$ is a $p-1$ lag polynomial. $p=2$ is the VAR lag length. We estimate the VAR in (1) for each age group separately: AMTR_t, URATE_t, and PRATE_t are age-specific AMTR, unemployment rate, and participation rate in year t, respectively, and $\mathbf{X}_t$ is a vector of aggregate control variables. We consider a sample of annual observations for the period 1961-2012.

Variables in $\mathbf{X}_t$ include the log of real GDP per capita, the log of the S&P index, and the federal funds rate, which allows us to capture business cycle dynamics, monetary policy stance, as well as the effects of bracket creep. To explicitly allow for the feedback from debt to taxes and spending, the log of real government spending per capita (purchases and net transfers), the average tax rate and the change in log real federal government debt per capita are also included: given the government's budget constraint, any change in tax rates must eventually lead to adjustments in other fiscal instruments.[5] Further, since tax changes are often motivated by concerns about government deficits and debt accumulation, the inclusion of a set of contemporaneous and past fiscal variables most likely provides relevant information to isolate the unanticipated innovations in tax rates.

However, difficulties may still arise to the extent that some of the tax changes classified as exogenous according to the Romer and Romer's classification are indeed due to population aging. We think that this type of concern does not apply to our exercise. According to the narrative records of post-war tax policy (see Romer and Romer, 2009), legislated tax changes are driven by considerations that are unrelated to population aging. Several other variables could enter the VAR. However, we note that omitted variables that are orthogonal to the fiscal variables (once lagged business cycle indicators are included in the VAR specification)

[5] Burnside et al. (2004) argue that the effects of shocks to government purchases may differ depending on the endogenous response of other fiscal instruments.

would not bias the estimated effects of changes in AMTR.

Estimation If the system in (1) generates unpredictable innovations to the vector of observables $\mathbf{Y}_t$, then the vector of such reduced-form innovations is a linear transformation of the underlying structural shocks $\epsilon_t \equiv \left[\epsilon_t^{\text{AMTR}}, \epsilon_t^{\text{URATE}}, \epsilon_t^{\text{PRATE}}, \epsilon_t^{\mathbf{X}}\right]'$, such that: (i) $\mathbb{E}\left[\epsilon_t\right] = 0$, (ii) $\mathbb{E}\left[\epsilon_t \epsilon_t'\right] = \Sigma_\epsilon$ is a diagonal matrix (we further impose $\Sigma_\epsilon \equiv I$, where I is the identity matrix), and (iii) $\mathbb{E}\left[\epsilon_t \epsilon_{t-j}'\right] = 0$ for $j \neq 0$. The vector of such structural shocks consists then of exogenous innovations in tax rates and other observables that are uncorrelated with each other. In the SVAR literature, the structural shocks ϵ_t are treated as latent variables that are estimated based on the prediction errors of the observables, $\mathbf{Y}_t$, conditional on the informational content in finite distributed lags of $\mathbf{Y}_t$, that is, $\mathbb{Y}_t \equiv \left[\mathbf{Y}_{t-1}', \ldots, \mathbf{Y}_{t-p}'\right]'$.

We posit that $e_t = \mathcal{H}\epsilon_t$, where $\mathcal{H}$ is a matrix of parameters that determines the impact response of the vector of observables, $\mathbf{Y}_t$, to the structural shocks, ϵ_t, we aim to identify. Specifically, we are interested in identifying the parameters in the first column of $\mathcal{H}$, that is, $\mathcal{H}^{i,1}$, with $i = 1, \ldots, \dim(\mathbf{Y}_t)$, that determine the impact response of the observables, $\mathbf{Y}_t$, to the shock to AMTR, ϵ_t^{AMTR}. Identification of $\mathcal{H}^{i,1}$ is achieved by imposing identifying restrictions and hinges on the availability of a proxy variable, m_t, for the latent structural shock to the tax rate, ϵ_t^{AMTR}, that jointly satisfies the identifying assumptions $\mathbb{E}\left[m_t \epsilon_t^{\text{AMTR}}\right] \neq 0$ and $\mathbb{E}\left[m_t \epsilon_t^i\right] = 0$ for $i \geq 2$ (the superscript " i " denotes the i-th element of the vector). The first orthogonality condition requires the proxy to be contemporaneously correlated with the underlying shock to the average marginal tax rate. The second orthogonality condition requires the proxy to be contemporaneously uncorrelated with all other structural shocks.

In our case, the age-specific proxies for exogenous tax changes are indicator variables that take on non-zero values at the time of an exogenous tax reform, and zero otherwise. The non-zero values are listed in column (3) through (8) of Table 1. When we estimate the proxy SVAR with aggregate variables only, the non-zero values are those in column (2).

Once the contemporaneous (or impact response) parameters are identified and estimated, the effects of a tax shock in subsequent years is traced out using the estimated system in (1). The resulting impulse response functions (IRF) measure the expected dynamic adjustment of the endogenous variables to the initial shock to the AMTR.

5 Aggregate Effects of Tax Shocks

In this section we establish new facts on the dynamic response of the U.S. labor market to unanticipated changes in tax rates. Notably, we consider two variables that are key indicators of state of the labor market, i.e. the aggregate unemployment and participation rate.

To interpret the aggregate results, it is useful to consider the following decomposition of the employment to population ratio:

$$\frac{\text{employment}}{\text{population}} = \underbrace{\left(1 - \frac{\text{unemployment}}{\text{employment+unemployment}}\right)}_{\text{1 minus the unemployment rate}} \times \underbrace{\left(\frac{\text{employment+unemployment}}{\text{population}}\right)}_{\text{participation rate}}.$$

This decomposition shows that employment as a fraction of the population of 16 years and older is equal to the employment rate (fraction of employed workers in the labor force, one minus the unemployment rate) times the participation rate. Hence, the response of the employment to population ratio to tax cuts is accounted by the response of either the unemployment rate or participation rate, or both.

Here we show that the unemployment rate is indeed quite responsive to tax cuts, whereas the participation rate is not. These results indicate that the response of the employment to population ratio is in fact the mirror image of the response of the aggregate unemployment rate. Unemployment, as opposed to participation, is the key margin for understanding the aggregate response of the labor market to unanticipated and temporary changes in AMTR.

5.1 Aggregate unemployment response

Panel A of Figure 3 shows that the estimated response of the AMTR to the tax shock is highly persistent. Specifically, AMTR remain below average up to 5 years after the shock. This high persistence contrasts with the relatively fast mean reversion observed for average personal income tax rates, as estimated by Mertens and Ravn (2013), but in line with Mertens and Ravn (2013), where they estimate the response of real GDP per capita to tax cuts using AMTR.

Panel B of Figure 3 shows the response of the unemployment rate to a 1 percentage point cut in AMTR. The estimates point to large aggregate effects of tax changes. Notably, the peak response, that occurs 1 year after the initial shock, implies that a 1 percentage point cut in AMTR leads to an approximately 0.7 percentage points decrease in the aggregate unemployment rate. In terms of the U.S. labor force (employed plus unemployed) in 2007, a decline of 0.7 percentage points in the unemployment rate amounts to nearly 1.1 million jobs, that are either preserved or created.

We note that a 1 percentage point cut in AMTR is not an unusual event as the standard deviation of the AMTR is 4.1 percent. These findings point then to highly significant and quantitatively large effects of tax changes on aggregate unemployment. The magnitude of these effects is somewhat greater than that found by Mertens and Ravn (2013) in response to exogenous changes in average effective tax rates on personal income. This observation suggests that unanticipated changes in marginal tax rates have larger effects than changes in average tax rates as they operate through incentive effects on intertemporal substitution.

5.2 Aggregate participation response

Panel C of Figure 3 shows the response of the aggregate participation rate to an equally-sized 1 percentage point cut in AMTR. In contrast with the results for the unemployment rate, the response of the participation rate is both statistically and economically insignificant. This finding is, perhaps, not surprising since the labor force participation rate has displayed pronounced low-frequency movements over the post-war period, arguably driven by long-run demographic trends that are hardly affected by the magnitude of the realized tax shocks. Yet, one cannot a priori dismiss the hypothesis that larger shocks to AMTR could generate a substantially different response in labor force participation. In that case, the main concern would be whether linear SVAR remain reliable in recovering the true dynamic response to large shocks.

6 Age-Specific Effects of Tax Shocks

In this section we detail the demographics of the U.S. labor market response to tax shocks. To this aim, we study if and the extent to which the dynamic responses of unemployment and participation rates to tax cuts vary by age. In doing so, it is imperative to keep in mind that the effects of a shock to AMTR on age-specific labor-market outcomes incorporate equilibrium feedback effects that result from the fact that changes in average marginal tax rates impact workers in all age groups, rather than just the specific age group considered.

Ultimately, we are interested in decomposing the response of the aggregate unemployment rate into the relative contribution of each age group, after all the equilibrium feedback effects have played out. This will allow us to quantify the relative importance of the young, prime-age, and old in shaping the aggregate response of the unemployment rate to tax cuts.

6.1 Age-specific unemployment response

We now turn to study the role of age-specific unemployment rates and labor force shares for the response of the aggregate unemployment rate. To this goal, we consider the following decomposition of the aggregate unemployment rate:

$$\frac{\text{unemployment}}{\text{labor force}} = \sum_a \underbrace{\frac{\text{labor force}_a}{\text{labor force}}}_{\substack{\text{age-specific} \\ \text{labor force share}}} \times \underbrace{\frac{\text{unemployment}_a}{\text{labor force}_a}}_{\substack{\text{age-specific} \\ \text{unemployment rate}}}, \tag{2}$$

where a indicates age and the labor force is defined as employed plus unemployed workers of 16 years and older, in accord with the definition used by the Bureau of Labor Statistics (BLS). The decomposition in (2) shows that the response of the aggregate unemployment rate to tax cuts is accounted by the response of either age-specific labor force shares or age-specific unemployment rates, or both. We show that age-specific unemployment rates are indeed responsive to tax cuts, whereas age-specific labor force shares are not.

Labor force shares vs. unemployment rates by age To disentangle the relative contribution of age-specific labor force shares from that of age-specific unemployment rates, we construct a counterfactual time series of the aggregate unemployment rate, u_t^{FLFS}, in which age-specific labor force shares are fixed at their sample averages, $\bar{\phi}_a^{\text{LF}}$, whereas age-specific unemployment rates, $u_{a,t}$, vary over time as in the data:

$$u_t^{\text{FLFS}} \equiv \sum_a \bar{\phi}_a^{\text{LF}} \times u_{a,t}, \text{ with } \sum_a \bar{\phi}_a^{\text{LF}} = 1. \tag{3}$$

We then re-estimate the proxy SVAR by replacing the actual unemployment and participation rate with the counterfactual unemployment rate in (3) and participation rate in (6). Panel B of Figure 4 shows that the impulse response to the AMTR shock of the counterfactual unemployment rate (dashed line with diamonds) is nearly indistinguishable from the impulse response of the actual unemployment rate (full line with circles). We conclude that age-specific unemployment rates, as opposed to age-specific labor force shares, are responsible for the response of the unemployment rate to a tax shock. As argued before, labor force shares by age display marked low-frequency movements in the post-war period. However, such low-frequency movements are due to the underlying demographic trends that pervade the entire U.S. economy, which are unlikely to be affected by temporary changes in marginal tax rates. The composition of the workforce is largely pre-determined by fertility decisions made prior to the observed changes in tax rates.

These findings are important for the scope of this paper as they provide an empirically-validated restriction, akin to an orthogonality condition, that will enable us to quantify the role of an aging labor force in shaping the aggregate unemployment response to tax cuts. Specifically, we can view the IRF of the aggregate unemployment rate as a *weighted* average of the IRF of the age-specific unemployment rates, where the weights are (sample averages of) the age-specific labor force shares:

$$\mathrm{IRF}(h) \approx \sum_{a} \bar{\phi}_a^{\mathrm{LF}} \times \mathrm{IRF}(a, h), \tag{4}$$

where h is the number of years after the initial shock to the AMTR. Note that the impulse response of the counterfactual unemployment rate, shown in panel B of Figure 4, guarantees that the right-hand side of (4) is indeed a strikingly good approximation of the impulse response of the actual unemployment rate, the left-hand side of (4). With this approximation result at hand, we decompose the contribution of each age group to the aggregate response to tax cuts. We note that if there was no heterogeneity in the IRF across age groups, then the labor force shares would become irrelevant as $\sum_a \bar{\phi}_a^{\mathrm{LF}} = 1$ by construction. Thus, changes in the age composition of the labor force affect the response of the aggregate unemployment rate insofar as the unemployment rate responses to tax cuts differ by age.

Unemployment rates by age We next establish that the response to tax cuts of the aggregate unemployment rate indeed masks substantial heterogeneity by age. Specifically, the unemployment rate response of the young is nearly twice as large as that of the prime-age and old workers in the labor force. This age-specific heterogeneity in the responsiveness to tax cuts is the channel through which shifts in the age composition of the labor force affect the response of the aggregate unemployment rate to tax cuts.

Figure 5 shows the responses of age-specific unemployment rates to an equally-sized 1 percentage point cut in AMTR. Impulse responses in each panel are obtained using the age-relevant AMTR to obtain the reduced-form residuals and the appropriate instrument to identify age-specific AMTR shocks. The estimates display stark differences in the responses of the young (16-34 age group), prime-age (35-54 age group), and old (55-64 age group). The unemployment rate of the 16-24 years old falls by 1.5 percentage points at the peak of the response, that occurs 1 year after the initial shock. The magnitude of the peak response is more than twice as large as that of the aggregate unemployment rate, that we report in panel A for sake of comparison. The unemployment rate of the 25-34 years old falls by approximately 0.8 percentage points, which is broadly consistent with the response of the aggregate unemployment rate. The peak responses of the age groups 35-44, 45-54, and 55-64, are instead nearly half as large as those of the 16-24 and 25-34 years old.[6] In Appendix B, Figure B.5 and B.6 show that these age differences in the unemployment rate responses to the tax shocks are statistically significant.

6.2 Age-specific participation response

We now turn to analyze the role of age-specific participation rates and population shares for the response of the aggregate participation rate. In Section 5, we argued that participation does not respond to tax shocks. Again, this lack of responsiveness may mask heterogeneity by age. To address this concern, we consider the following decomposition of the aggregate participation rate:

$$\frac{\text{labor force}}{\text{population}} = \sum_a \underbrace{\frac{\text{population}_a}{\text{population}}}_{\substack{\text{age-specific} \\ \text{population share}}} \times \underbrace{\frac{\text{labor force}_a}{\text{population}_a}}_{\substack{\text{age-specific} \\ \text{participation rate}}}. \tag{5}$$

Next, we show that age-specific population shares are in fact unimportant in accounting for the response of the aggregate participation rate. And that the participation rates for all age groups are indeed unresponsive to the identified shocks to AMTR.

Population shares vs. participation rates by age To disentangle the contribution of age-specific population shares from age-specific participation rates, we use a counterfactual series of the aggregate participation rate, n_t^{FPS}, in which age-specific population shares are fixed at their sample averages, $\bar{\phi}_a^{\text{P}}$, whereas age-specific participation rates, $n_{a,t}$, vary over

[6] Note that these differences in responses remain if instead of using age-specific AMTR, one uses aggregate AMTR. See Figure B.4 in Appendix B.

time as in the data:

$$n_t^{\text{FPS}} \equiv \sum_a \bar{\phi}_a^{\text{P}} \times n_{a,t}, \text{ with } \sum_a \bar{\phi}_a^{\text{P}} = 1. \tag{6}$$

We estimate the SVAR by replacing the actual unemployment and participation rate with the counterfactual with fixed labor force and population shares as in (3) and (6), respectively. In Figure 4, panel C shows that the impulse response of the counterfactual participation rate (dashed line with diamonds) is indistinguishable from the impulse response of the actual participation rate (full line with circles). Thus, we conclude that the age-specific population shares are indeed irrelevant for the response of the aggregate participation rate to tax shocks.

Participation rates by age Figure 6 shows IRF of the age-specific participation rates to an equally-sized 1 percentage point cut in age-specific AMTR. The responses of all groups, young (16-24 and 25-34), prime-age (35-44, and 45-54) and old (55-64) are not statistically insignificant.[7]

7 Demographic Change and Tax Policy

In this section we build on the empirical evidence in Section 5 and 6 to quantify the role of demographic change for the effects of tax cuts on the aggregate unemployment rate. We adopt a *quantitative accounting* approach that consists of two steps. First, we measure the relative contribution of each age group to the average response of the aggregate unemployment rate to tax cuts. Second, we quantify by how much the aggregate impact of a tax cut changes when we account for the shifts in the age composition of the labor force observed in the data.

7.1 Quantifying the role of age composition

We now turn to quantify the contribution of each age group to the response of the aggregate unemployment rate to tax shocks. To this goal, we decompose the impulse response of the aggregate unemployment rate into additive shares that measure the relative contribution of each group to the aggregate response.

Contribution to the aggregate response by age Using the approximation in (4), each age group accounts for $\mathbf{share}_h^a$ of the response of the aggregate unemployment rate h

[7] Similar results hold if one uses the aggregate AMTR. See Figure B.7 in Appendix B.

years after the shock:

$$\mathbf{share}_h^a \equiv \bar{\phi}_a^{\mathrm{LF}} \times \frac{\mathrm{IRF}(a,h)}{\mathrm{IRF}(h)}, \text{ with } \sum_a \mathbf{share}_h^a = 1. \tag{7}$$

Table 2 shows that young individuals, identified by the age group 16-34, account for about two thirds of the aggregate response on impact and one year after the shock. At the same horizon, the age groups 16-34 and 35-54 account for nearly 93 percent of the aggregate response on impact, and for 91 percent of the response a year after the shock. The age groups 55-64 and 65+, combined, account for the remaining 7 percent of the impact response and 9 percent of the lagged.

How much of the age differences in $\mathbf{share}_h^a$ is due to differences in labor force shares versus differences in the ratio of IRF? To answer this question, we use an alternative decomposition in which the labor force shares are set to be the same across age groups, so that $\bar{\phi}_a^{\mathrm{LF}} = 1/n_a$, where n_a is the number of age groups:

$$\mathbf{share}_h^{a,\mathrm{FLFS}} \equiv \frac{1}{n_a} \times \frac{\mathrm{IRF}(a,h)}{\mathrm{IRF}(h)}. \tag{8}$$

Note that now any age-specific heterogeneity in $\mathbf{share}_h^{a,\mathrm{FLFS}}$ comes exclusively from the heterogeneity in the unemployment rate responses to tax cuts across different age groups. Thus, the difference between the shares with and without fixed labor force shares can be entirely attributed to the age composition of the labor force.

Indeed, Table 3 points to a quantitatively important role of age composition. Specifically, the two extended age groups 16-34 and 35-54 now account for approximately 83 percent of the aggregate unemployment response on impact and 82 percent of the response a year after the shock. These figures are considerably smaller than those in Table 2. Age composition alone is responsible for a decrease of nearly 10 percentage points. Most of these differences are due to the changes in the relative shares of the age groups 25-34 and 35-44 that represent, on average, roughly 47 percent of the U.S. labor force for the period 1961-2012.

Unemployment elasticities by age We now study the extent to which the age-specific heterogeneity in the unemployment rate responsiveness to a tax shock can be attributed to differences in unemployment elasticities across age groups versus differences in average unemployment rates. To this goal, we use a slightly modified version of (7):

$$\textbf{share}_h^a \equiv \bar{\phi}_a^{\text{LF}} \times \frac{\bar{u}_a}{\bar{u}} \times \frac{\epsilon_{a,h}^u}{\epsilon_h^u}, \tag{9}$$

where $\bar{u}_a$ and $\bar{u}$ are averages of age-specific and aggregate unemployment rates, respectively. To estimate aggregate, ϵ_h^u, and age-specific unemployment rate elasticities, $\epsilon_{a,h}^u$, we estimate the proxy SVAR using the AMTR and unemployment and participation rates in logs, with aggregate variables and separately for each age group. According to (9), the share of each group equals the ratio of the age-specific to the aggregate unemployment rate elasticity, weighted by the product of (i) the age-specific labor force share and (ii) the ratio of the age-specific to the aggregate average unemployment rate.

A well-known pattern is that average unemployment rates decrease monotonically with age. This fact has been successfully explained by theories of worker turnover and life-cycle unemployment (see Jovanovic, 1979; Chéron et al., 2013; Esteban-Pretel and Fujimoto, 2014; Papageorgiou, 2014; Gervais et al., 2016; Menzio et al., 2016). As shown in Table 5, these age differences are large.

Table 4 establishes new facts on the life-cycle profile of the unemployment rate elasticities to tax shocks. The estimates provide evidence of substantial age heterogeneity. Notably, the age group 16-34 features an impact elasticity that is nearly twice as large as that of the age group 55 years and older and 30 percent higher than the age group 35-54.

In our view, these age differences in unemployment elasticities can be instrumental in disciplining theories of life-cycle unemployment, as they provide overidentifying restrictions for quantitative analysis of taxes and unemployment. We further stress that these empirical results also complement the well-known observation that business cycle volatility in labor-market outcomes declines with age (see Clark and Summers, 1981; Gomme et al., 2005; Jaimovich and Siu, 2009; Jaimovich et al., 2013).

7.2 Quantifying the role of demographic change

We now turn to evaluate the quantitative implications of the aging of the baby boomers for the propagation of tax cuts in the United States. Our approach builds on Shimer (1999) and Jaimovich and Siu (2009), where the authors quantify the role of age composition of the U.S. workforce for the low-frequency movements in the aggregate unemployment rate and cyclical volatility in hours worked, respectively.[8] Here, we show that demographic change has quantitatively important implications for the effectiveness of tax policy. To establish this result, we implement a quantitative accounting exercise. Specifically, we re-construct the U.S. history of aggregate unemployment responses to a tax cut, by using age-specific labor force shares and unemployment rates observed at a specific point in time, and the unemployment rate elasticities estimated over the sample period 1961-2012, as shown in Table 4. The implied unemployment responses provide a quantitative accounting of how the trends in the age composition of the labor force affect the response of the aggregate unemployment rate to tax cuts.

We construct an aggregate unemployment response to tax cuts, that is adjusted for age composition (AC-adj), as follows:

$$du_{h,t}^{\text{AC-adj}} \equiv \sum_{a=16}^{65+} \phi_{a,t}^{\text{LF}} \times \bar{u}_{a,t} \times \epsilon_{a,h}^{u}, \tag{10}$$

where the time subscripts indicate that the AC-adj response may vary over time due to the observed changes in the age composition of the labor force. Specifically, we use equation (10) to generate unemployment responses to an across-the-board 1 percentage point tax cut, at 5-year intervals, from 1950 to 2005.

Before discussing the results, it is worth notice that this exercise assumes the absence of indirect effects from tax cuts to the age composition of the labor force. This assumption is empirically verified by the results in Section 5 and 6: labor force shares are unresponsive to tax cuts. The responses in (10) then measure what would have been the response of the aggregate unemployment rate to a tax cut, if the age composition was that of a specific year in the sample. Hence, given the change in the age composition of the U.S. labor force over the post-war period, the aggregate unemployment response to tax cuts varies over time.

Figure 7 shows the AC-adjusted responses of the aggregate U.S. unemployment rate on impact and a year after the shock. Same patterns hold up to four years after the shock. Note that larger negative values indicate that an equally-sized 1 percentage point cut in

[8] The results in Shimer (1999) indicate that the observed trends in the age composition of the labor force have an impact on the *level* of the aggregate U.S. unemployment rate. The entry of the baby boomers in the labor force in the late-1970s, and their aging, accounts for a substantial fraction of the rise and fall in unemployment rates observed in past 50 years. Jaimovich and Siu (2009) argue that the age composition of the labor force has a causal impact on the *volatility* of hours worked over the business cycle. Since young workers feature less volatile hours worked than prime-age, the aging of the labor force accounts for a significant fraction of the decrease in business cycle volatility observed since the mid-1980s in the United States over the so-called Great Moderation.

AMTR reduces aggregate unemployment by more. The results indicate large changes in the response of the aggregate unemployment rate to tax cuts. The largest impact and lagged responses occur in the mid-1970s. The peak impact response to a 1 percentage point cut is 0.59 percentage points, that is 42 percent larger than the response of 0.34 percentage points in 2005, whereas the peak lagged response is 0.84 percentage points, that is 38 percent higher than the 0.52 percentage points in 2005. Overall, the magnitude of the counterfactual responses is nearly constant from the mid-1950s to the early-1970s, it markedly increases (in absolute value) during the mid-1970s, and starts to steadily decrease since then.

Importantly, this time variation in aggregate unemployment responsiveness lines up nicely with the baby boom and baby bust phenomena we described in Section 2. The entry of the baby boomers in the labor force in the 1970s led to a nearly 10 percentage points increase in the share of the 20-34 years old. Since the young are more responsive to tax cuts than prime-age and old workers, the responsiveness of the aggregate unemployment rate dramatically increased over that period. However, as the aging of the baby boomers unfolds, the effects of tax cuts on the aggregate unemployment rate are reduced to a level comparable to that of the early-1950s.

8 Conclusion

In this paper we investigate the consequences of population aging for the transmission of tax changes to the aggregate labor market in the United States. After isolating exogenous variation in average marginal tax rates in SVAR, using a narrative identification approach, we document that the responsiveness of unemployment rates to tax changes largely varies across age groups: the unemployment rate response of the young is nearly twice as large as that of the old. This heterogeneity is the channel through which shifts in the age composition of the labor force impact the response of the aggregate U.S. unemployment rate to tax changes. We find that the aging of the baby boomers considerably reduces the effects of tax cuts on aggregate unemployment.

Table 1: Estimated Impact of Selected Tax Reforms

		Impact on average marginal tax rates (percentage points)							
		All MMO	All FF	16-24	25-34	35-44	45-54	55-64	65+
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	in year								
Revenue Act of 1964	1964	−2.61	−2.26	−1.95	−2.07	−2.30	−2.40	−2.39	−2.34
Revenue Act of 1978	1979	−1.35	−1.91	−2.01	−1.90	−1.97	−1.83	−1.87	−1.91
Economic Recovery Tax Act 1981	1981	−0.31	−0.36	−0.25	−0.35	−0.39	−0.41	−0.37	−0.26
Tax Reform Act of 1986	1987	−2.41	−4.18	−2.37	−4.08	−4.66	−4.56	−4.37	−2.92
Omnibus Budget Reconciliation Act of 1990	1991	0.79	0.44	0.05	0.33	0.55	0.57	0.46	0.42
Omnibus Budget Reconciliation Act of 1993	1993	1.08	0.12	0.02	0.10	0.13	0.14	0.13	0.17
Jobs and Growth Tax Relief Reconciliation Act of 2003	2003	−1.95	−2.49	−1.12	−2.50	−2.66	−2.62	−2.51	−2.28

Notes: "All MMO" refers to the aggregate AMTR as calculated by Mertens and Montiel-Olea (2018). "All FF" refers to the aggregate AMTR based on authors' calculations.

Table 2: Shares of Unemployment Response by Age

h (years after shock):	0	1	2	3
$\mathbf{share}_h^{16\text{-}24}$	40.06	36.09	35.52	−3.35
$\mathbf{share}_h^{25\text{-}34}$	28.18	23.66	18.59	−28.18
$\mathbf{share}_h^{35\text{-}44}$	12.62	16.26	15.73	20.08
$\mathbf{share}_h^{45\text{-}54}$	11.88	15.11	17.66	69.42
$\mathbf{share}_h^{55\text{-}64}$	6.08	7.53	10.06	34.80
$\mathbf{share}_h^{65+}$	1.18	1.32	2.44	7.23

Notes: See equation (7) for the definition of $\mathbf{share}_h^a$. Shares are reported in percent such that $\sum_{a=16}^{65+} \mathbf{share}_h^a = 100$.

Table 3: Counterfactual Shares of Unemployment Response by Age

h (years after shock):	0	1	2	3
$\mathbf{share}_h^{16\text{-}24,\mathrm{FLFS}}$	40.96	36.39	33.48	−2.31
$\mathbf{share}_h^{25\text{-}34,\mathrm{FLFS}}$	22.05	18.25	13.41	−14.92
$\mathbf{share}_h^{35\text{-}44,\mathrm{FLFS}}$	10.25	13.02	11.78	11.03
$\mathbf{share}_h^{45\text{-}54,\mathrm{FLFS}}$	11.29	14.15	15.46	44.65
$\mathbf{share}_h^{55\text{-}64,\mathrm{FLFS}}$	9.39	11.46	14.31	36.37
$\mathbf{share}_h^{65+,\mathrm{FLFS}}$	6.06	6.71	11.53	25.18

Notes: See equation (8) for the definition of $\mathbf{share}_h^{a,\mathrm{FLFS}}$. Shares are reported in percent such that $\sum_{a=16}^{65+} \mathbf{share}_h^{a,\mathrm{FLFS}} = 100$.

Table 4: Unemployment Elasticities by Age

Age group:	16+	16-24	25-34	35-44	45-54	55-64	65+	16-34	35-54
Impact elas.	1.52	2.14	2.63	1.49	1.79	1.47	1.24	2.16	1.66
Lagged elas.	2.79	2.59	3.42	3.00	3.68	3.13	1.92	2.97	2.06

Notes: "Impact elas." refers to the unemployment rate elasticity of a specific age group at horizon $h = 0$; "Lagged elas." refers to the unemployment rate elasticity of a specific age group at horizon $h = 1$ (one year after the shock). Each of the impact and lagged elasticities estimates are based on a separate SVAR system that includes the log of the unemployment and the participation rate of a specific age group and a common set of regressors as specified in (1). Elasticities are with respect to each age-specific average marginal tax rate (AMTR) and reported in percent.

Table 5: Unemployment Rates and Labor Force Shares by Age

Age group:	16+	16-24	25-34	35-44	45-54	55-64	65+
Avg. UNR	6.09	12.48	5.82	4.44	3.91	3.78	3.71
Avg. UNR-ratio	1	2.04	0.95	0.72	0.64	0.62	0.61
Avg. LFS	100	18.17	23.74	22.87	19.56	12.04	3.62

Notes: Average unemployment rate (UNR) and labor force share (LFS), for 1961-2012, are reported in percent. The second row indicates average unemployment rates by age, relative to that of 16+ years old (UNR-ratio).

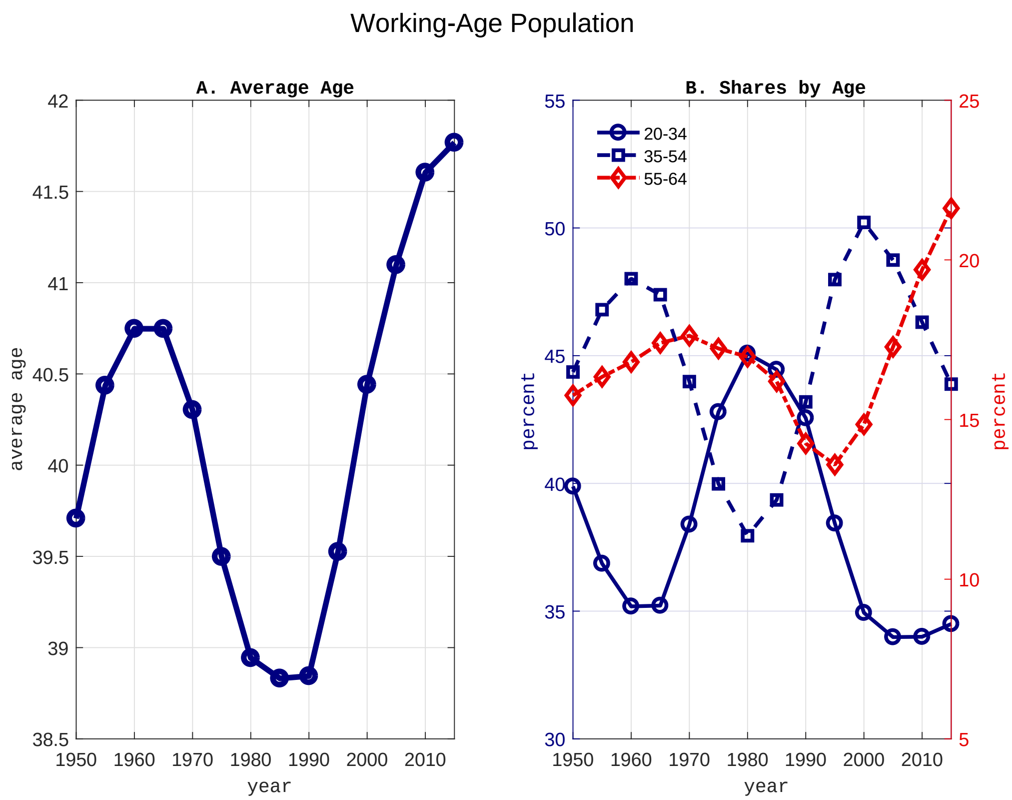

Figure 1: Trends in the Age Composition of the U.S. Population, 1950-2015

Notes: Panel A shows the average age of the U.S. civilian noninstitutional population (20-64 years old). The average age of the population is calculated as $\bar{a}^{\mathrm{P}} \equiv \sum_{a \in A} \left(\frac{\underline{a}+\bar{a}}{2}\right) \phi_a^{\mathrm{P}}$, where $\underline{a}$ and $\bar{a}$ are respectively lower and upper bounds of the age group $a \in A$, with $A = \{20\text{-}24, 25\text{-}34, 35\text{-}44, 45\text{-}54, 55\text{-}64\}$, and ϕ_a^{P} is the age-specific population share (the ratio of the population in the age group a to total population). Panel B shows the population shares by three age groups: (i) full line with circles (left axis) shows $\phi_{20\text{-}24}^{\mathrm{P}} + \phi_{25\text{-}34}^{\mathrm{P}}$; (ii) dashed line with squares (left axis) shows $\phi_{35\text{-}44}^{\mathrm{P}} + \phi_{45\text{-}54}^{\mathrm{P}}$; and (iii) dashed-dotted line with diamonds (right axis) shows $\phi_{55\text{-}64}^{\mathrm{P}}$.

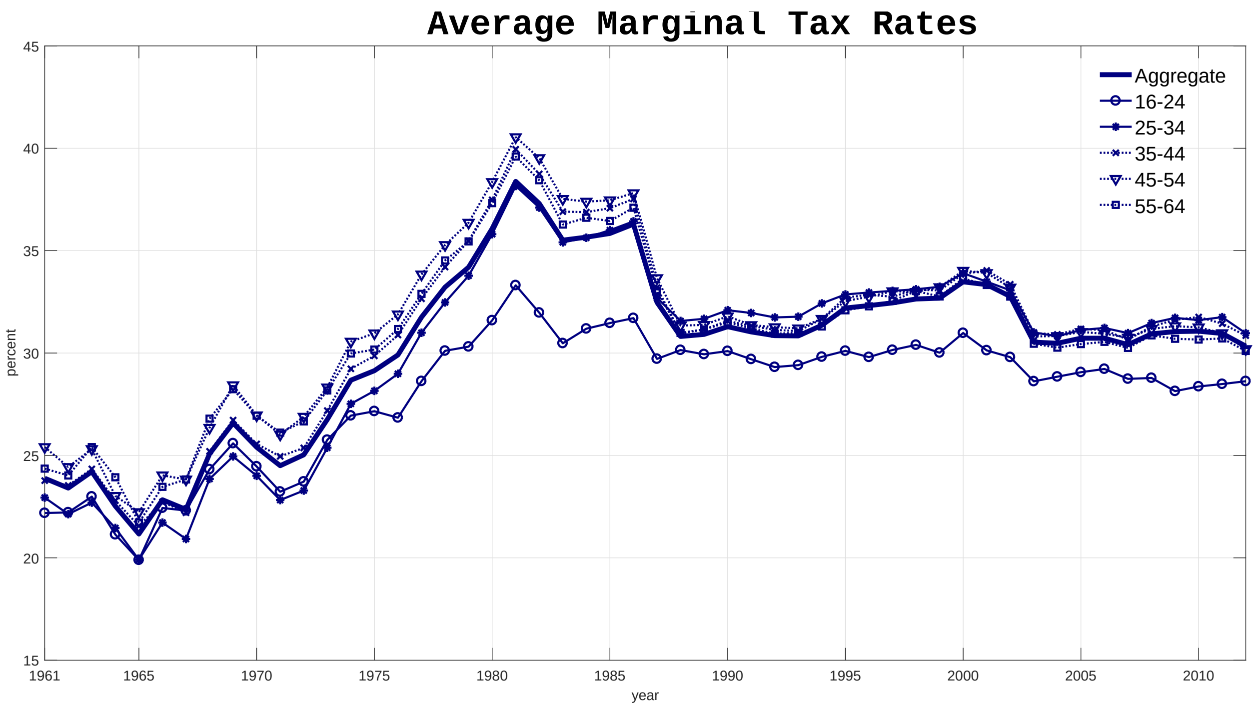

Figure 2: Average Marginal Tax Rates, 1961-2012

Notes: The figure shows the time series of average marginal tax rates (AMTR), aggregate and by age groups. AMTR includes the average marginal individual income tax rate (AMIITR) and average marginal payroll tax rate (AMPTR).

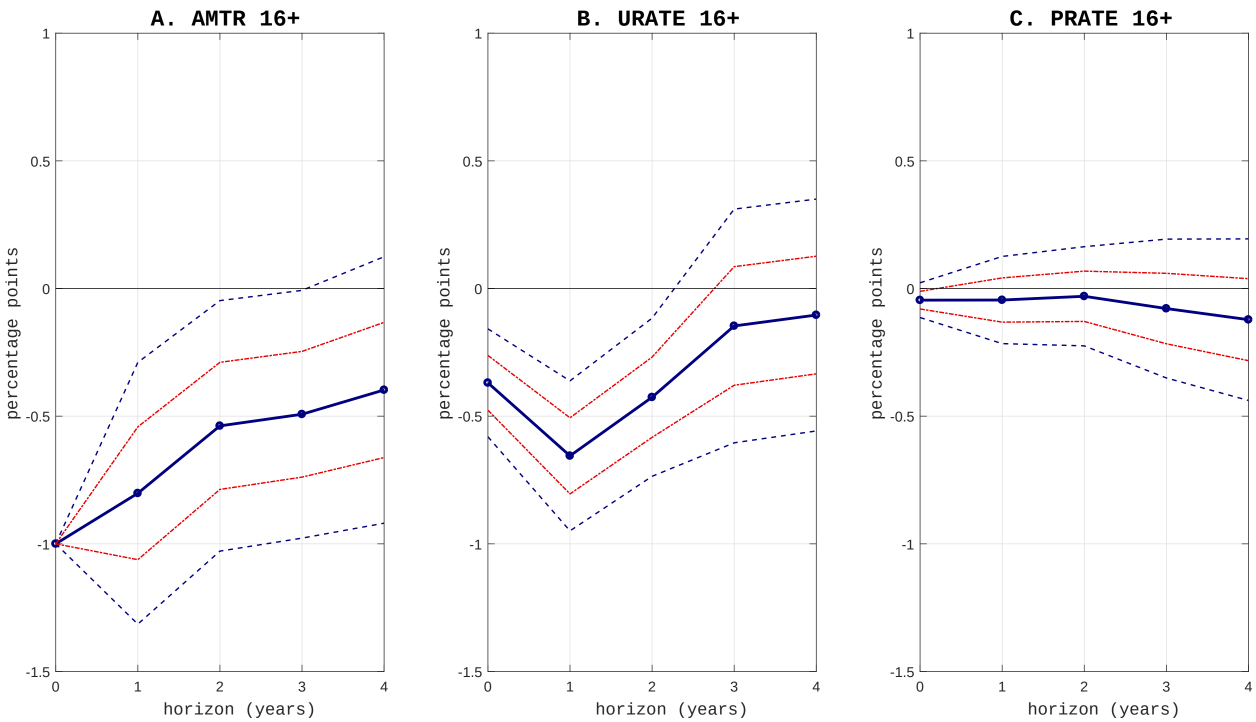

Figure 3: Unemployment and Participation Rate Response to a Tax Cut

Notes: The figure shows the response to a 1 percentage point cut in the average marginal tax rate (AMTR). Full lines with circles are point estimates; dash-dotted lines are 68 percent confidence bands; dashed lines are 95 percent confidence bands. Both intervals are computed using the Delta-method suggested by Montiel-Olea et al. (2017) with a Newey and West (1987) HAC-robust residual covariance matrix.

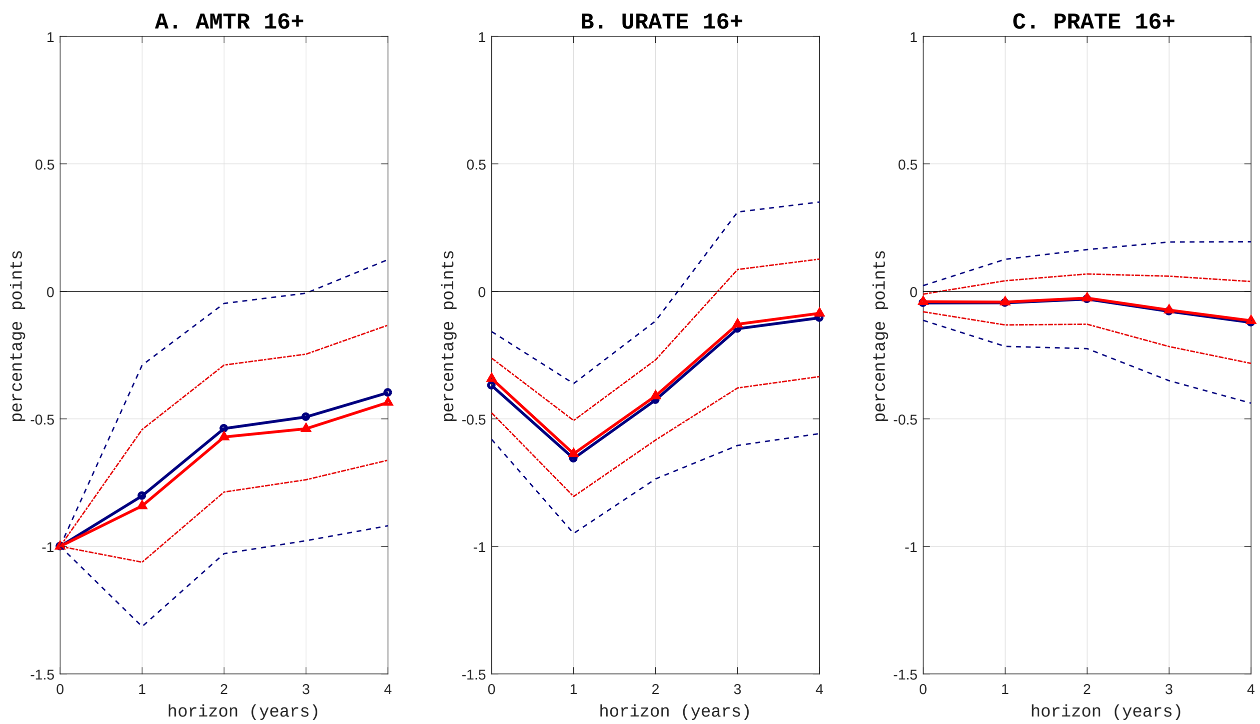

Figure 4: Actual Data vs. Counterfactual Series

Notes: Full lines with circles are point estimates for the response of the actual unemployment rate and participation rate to a 1 percentage point cut in the average marginal tax rate (AMTR); dash-dotted lines are 68 percent confidence bands; dashed lines are 95 percent confidence bands. Both intervals are computed using the Delta-method suggested by Montiel-Olea et al. (2017) with a Newey and West (1987) HAC-robust residual covariance matrix. Full lines with diamonds show the response estimated with the counterfactual unemployment and participation rate, as implied by (3) and (6), respectively.

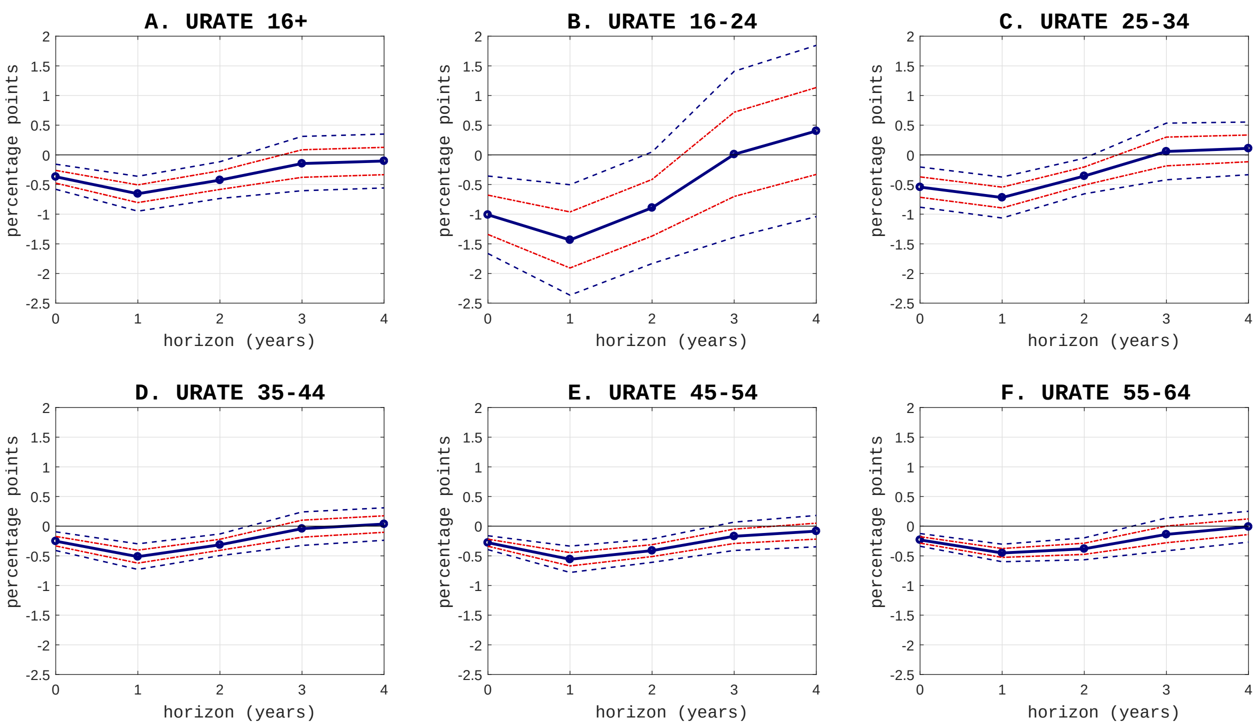

Figure 5: Unemployment Rate Response to a Tax Cut by Age

Notes: The figure shows the response to a 1 percentage point cut in the age-specific average marginal tax rate (AMTR). Full lines with circles are point estimates; dash-dotted lines are 68 percent confidence bands; dashed lines are 95 percent confidence bands. Both intervals are computed using the Delta-method suggested by Montiel-Olea et al. (2017) with a Newey and West (1987) HAC-robust residual covariance matrix.

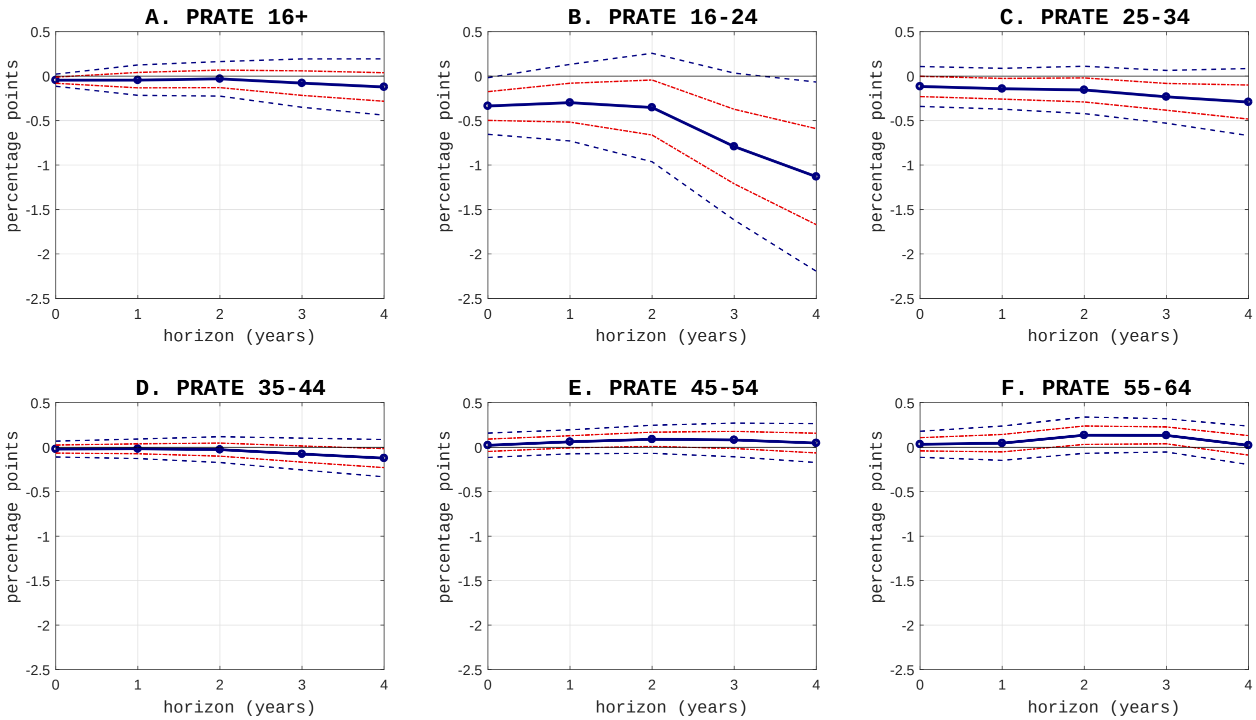

Figure 6: Participation Rate Response to a Tax Cut by Age

Notes: The figure shows the response to a 1 percentage point cut in the age-specific average marginal tax rate (AMTR). Full lines with circles are point estimates; dash-dotted lines are 68 percent confidence bands; dashed lines are 95 percent confidence bands. Both intervals are computed using the Delta-method suggested by Montiel-Olea et al. (2017) with a Newey and West (1987) HAC-robust residual covariance matrix.

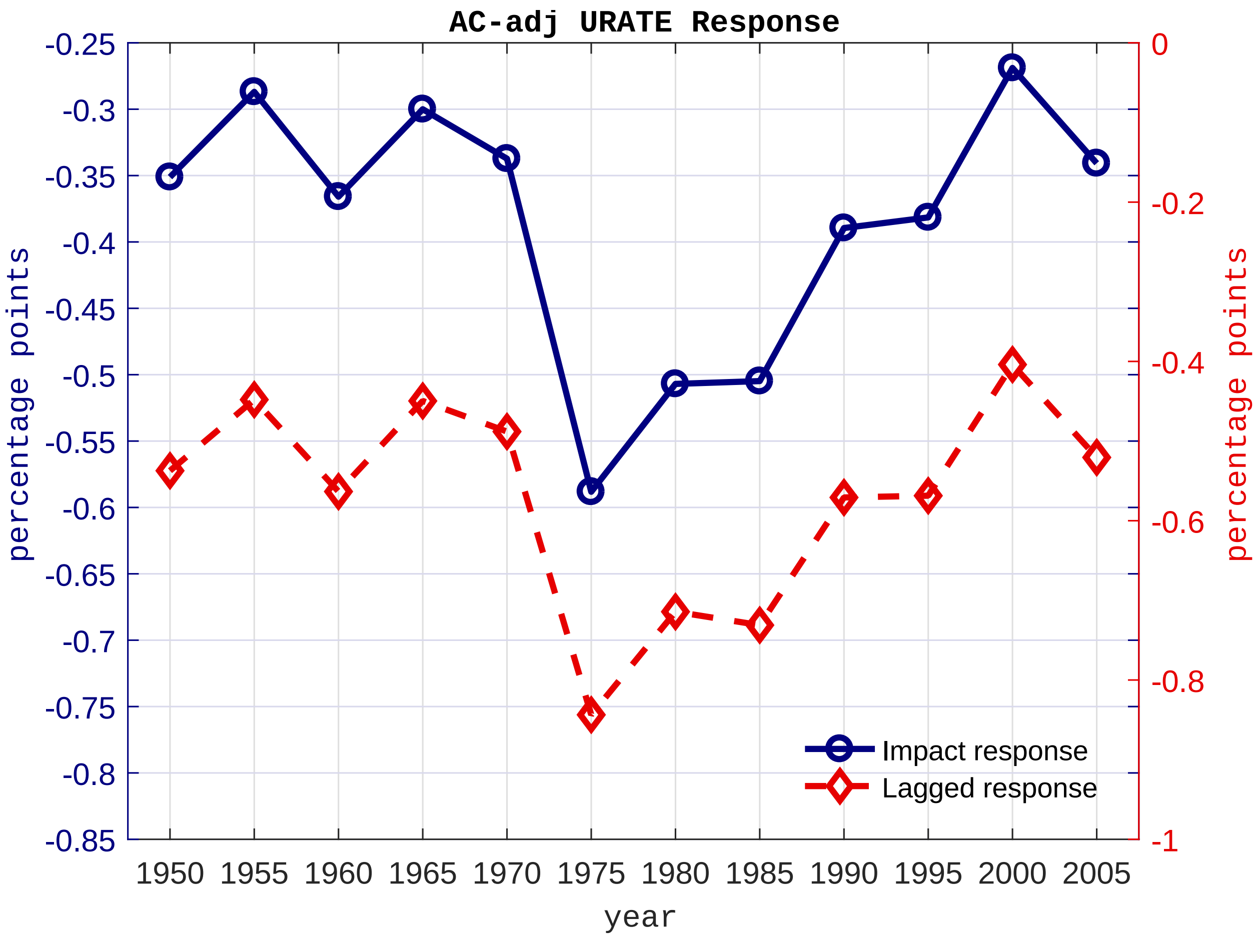

Figure 7: Demographic Change and Unemployment Rate Response to a Tax Cut

Notes: The figure shows the AC-adjusted responses of the unemployment rate of 16 years and older to a 1 percentage point cut in the average marginal tax rate (AMTR) for all age groups. "Impact response," full line with circles (left axis), shows the AC-adjusted response of the unemployment rate at horizon $h = 0$; "Lagged response," dashed line with diamonds (right axis), shows the AC-adjusted response of the unemployment rate at horizon $h = 1$ (one year after the shock). AC-adjusted responses are constructed using (10).

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Online Appendix

A Data

A.1 Marginal tax rates

This section details how we constructed average marginal tax rates (AMTR) for 1961-2012. Consistently with Barro and Redlick (2011) and Mertens and Montiel-Olea (2018), AMTR (both aggregate and age-specific) is calculated as the sum of the average marginal individual income tax rate (AMIITR) and the average marginal payroll tax rate (AMPTR). Figure A.1 and A.2 show time series of the aggregate and age-specific AMIITR and AMPTR.

A.1.1 Average marginal individual income tax rates

To calculate AMIITR we follow the procedure in Barro and Redlick (2011), and most of the literature thereafter. AMIITR, both aggregate and by age group, is based on a broad concept of labor income that includes wages, self-employment, partnership, and S-corporation. Our income source is the March supplement of the CPS. The March supplement contains income information (INCWAGE, INCBUS, and INCFARM) and demographic characteristics, such as age, marital status, and the number of children in the household. Data are extracted from IPUMS. NBER TAXSIM program simulates marginal tax rates given data inputs on income and demographic characteristics. Aggregate and age-specific AMTR are calculated as a weighted average of individual AMTR using adjusted gross income (AGI) as weights. Our aggregate AMTR displays a correlation of 0.92 in levels (and 0.90 in first-difference) with the AMTR calculated by Barro and Redlick (2011) as extended by Mertens and Montiel-Olea (2018).

A.1.2 Average marginal payroll tax rates

Based on Barro and Sahasakul (1983), AMPTR are calculated as

$$\text{AMPTR} = w_1 \left(\frac{s_f + s_w}{1 + s_f} \right) + w_2 s_e, \tag{A.1}$$

where s_f, s_w, and s_e are the contribution rates paid by employers, employee, and self-employed, respectively, and w_1 and w_2 are total taxable earnings of those with earnings below the annual maximum taxable as a ratio of total income. Data on contribution rates and maximum taxable earnings are available from the Annual Statistical Supplement at http://www.ssa.gov/policy/docs/statcomps/supplement/. The number of employees and self-employed is obtained from the BLS at https://www.bls.gov/spotlight/2016/self-employment-in-the-united-states/home.htm. The BLS publication "Self-employment In The United States" provides detailed statistics for the aggregate economy and age-specific groups from 1994 onward. To obtain estimates of the years prior to 1994, we use the 1994 observation and impute it backward until the beginning of the sample. Our estimates are robust to alternative imputation choices. For instance, assuming that the share of self-employed in each age group equals the share of self-employed in the aggregate has little impact on the calculations prior 1994. Our aggregate AMPTR displays a 0.97 (0.87) correlation with the level (first-difference) of the AMPTR calculated by Barro and Redlick (2011) as extended by Mertens and Montiel-Olea (2018).

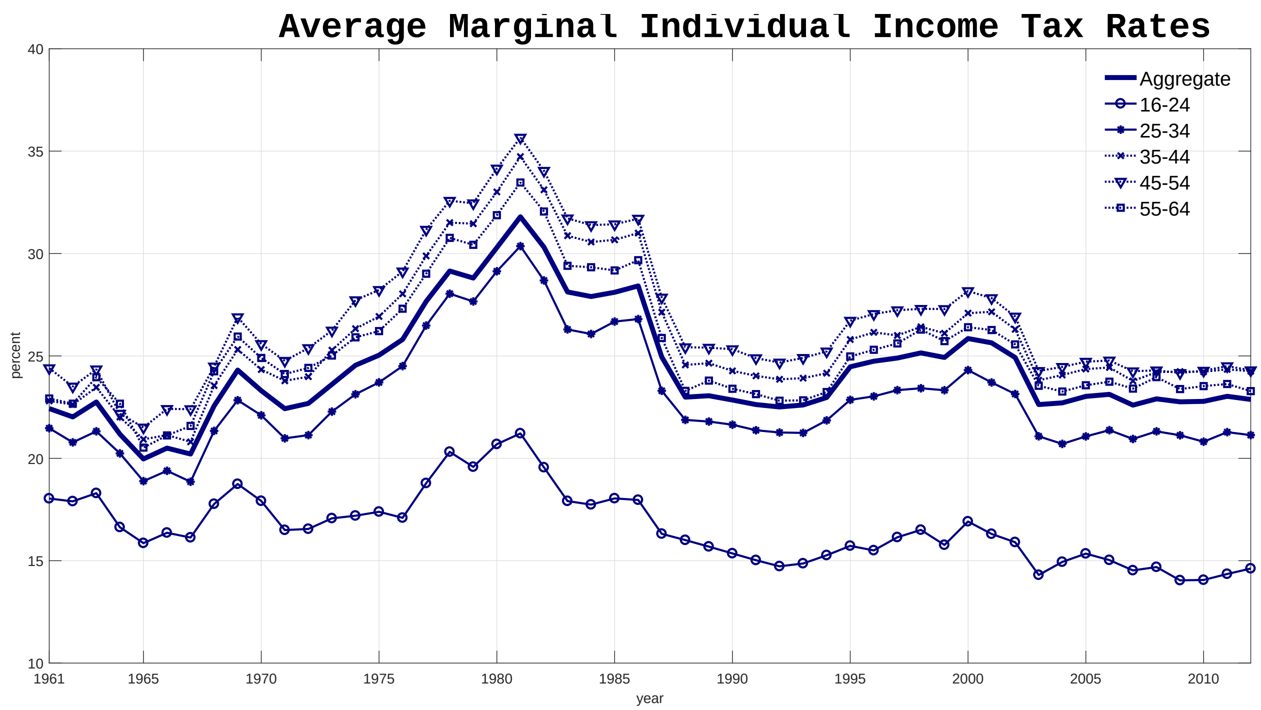

Figure A.1: Average Marginal Individual Income Tax Rates, 1961-2012

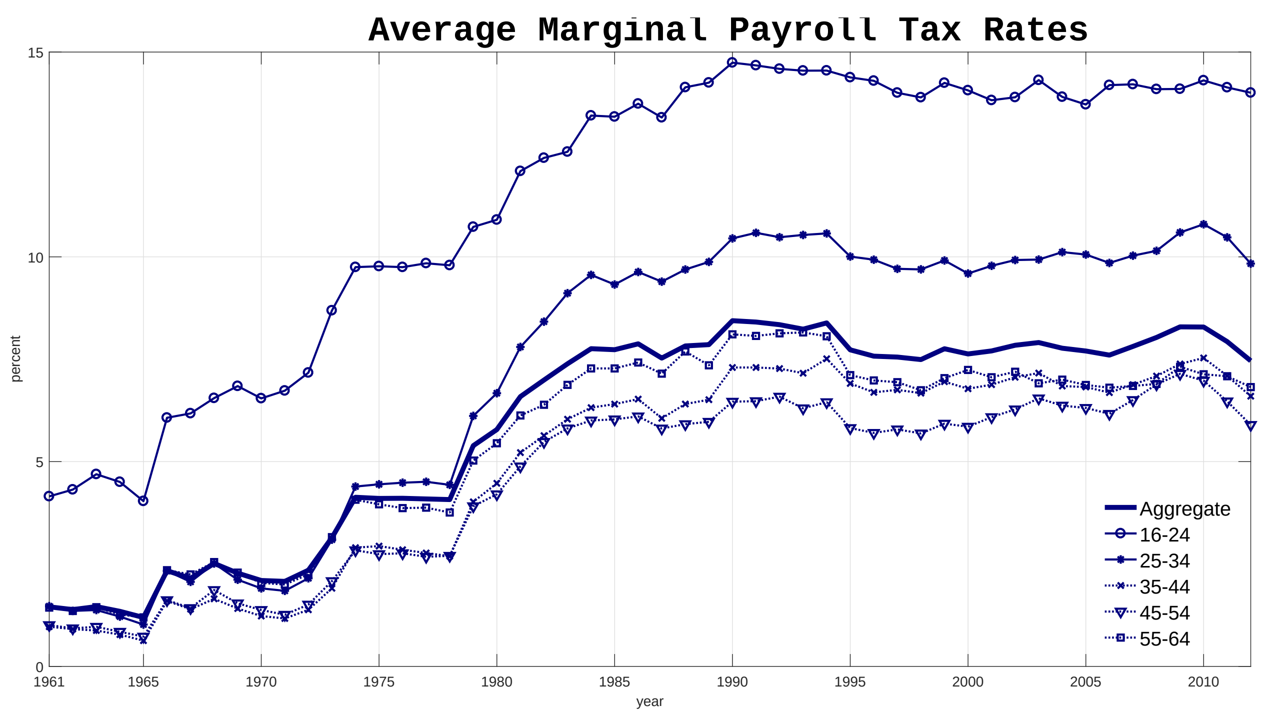

Figure A.2: Average Marginal Payroll Tax Rates, 1961-2012

A.2 Other time series

Real GDP per tax unit is NIPA 1.1.3 line 1 divided by potential tax units. The **Federal Funds Rate** is the annual average effective federal funds rate from the Federal Reserve Board of Governors. **Government Debt** per tax unit is federal debt held by the public, measured by Table L.106 line 19 (federal government, liabilities, credit market instruments) in the US Financial Accounts (release Z.1 of the Federal Reserve Board), divided by the log change in the BLS CPI Research Series Using Current Methods (CPI-U-RS) and potential tax units. **Government Spending** per tax unit is the sum of federal government purchases, net interest rate expenditures and net transfers (NIPA 3.2 line 46 less lines 3,4,7,10 and 11 plus NIPA 3.12U line 25), divided by the CPI-U-RS and potential tax units. The **Real Stock Price** is the S&P composite index from updates of Shiller (2000), divided by the CPI-U-RS. The **Average Tax Rate** is the sum of federal personal current taxes and contributions for social insurance (NIPA 3.2 line 3 plus NIPA 3.7 lines 3 and 21) divided by total market income from Piketty and Saez (2003). The **labor force** is the number of employed plus unemployed persons. The **unemployment rate** is the number unemployed divided by labor force. The **participation rate** is labor force divided by population. **Population** is the civilian noninstitutional population of 16 years of age and older. Data for the labor force, unemployment rate, participation rate, numbers of employed and unemployed, and population for the total economy and by age groups are obtained from the CPS, published by the BLS and available at the CPS home page at http://www.bls.gov/cps/.

B Additional Evidence

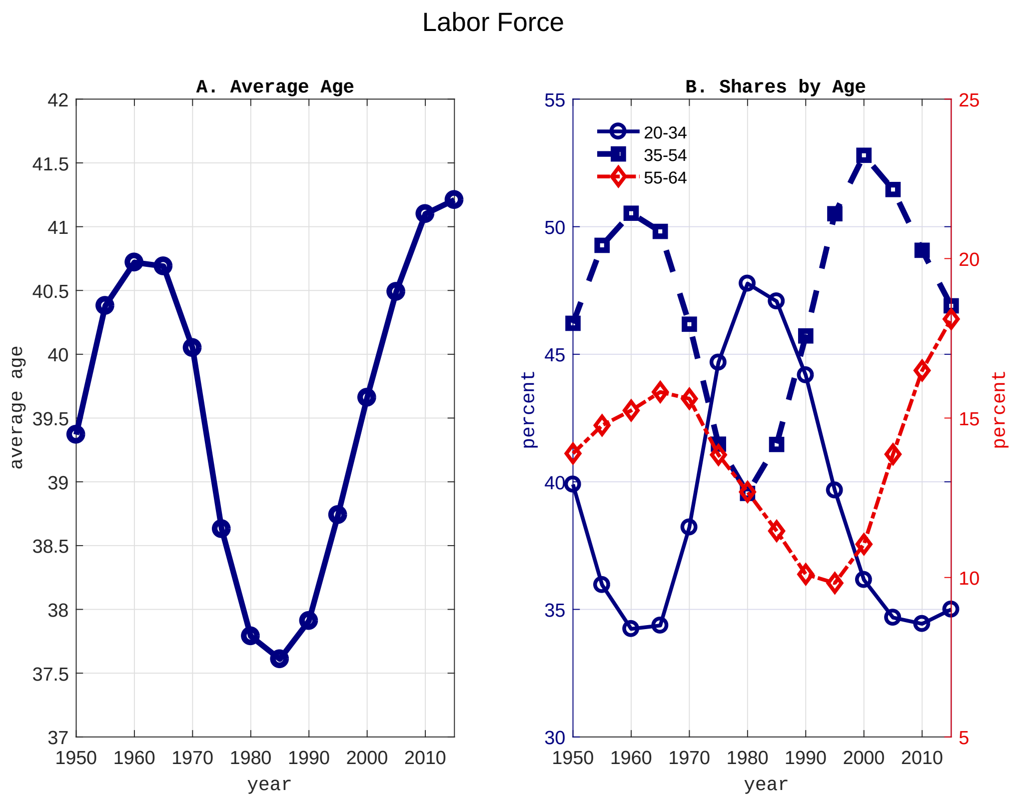

Figure B.1: Trends in the Age Composition of the U.S. Labor Force, 1950-2015

Notes: Panel A shows the average age of the U.S. labor force (employed plus unemployed workers of 20-64 years old). The average age of the labor force is calculated as $\bar{a}^{\mathrm{LF}} \equiv \sum_{a \in A} \left(\frac{\underline{a}+\overline{a}}{2} \right) \phi_a^{\mathrm{LF}}$, where $\underline{a}$ and $\overline{a}$ are respectively lower and upper bounds of the age group $a \in A$, with $A = \{20\text{-}24, 25\text{-}34, 35\text{-}44, 45\text{-}54, 55\text{-}64\}$, and ϕ_a^{LF} is the age-specific labor force share (the ratio of the labor force in the age group a to total labor force). Panel B shows the labor force shares by three age groups: (i) full line with circles (left axis) shows $\phi_{20\text{-}24}^{\mathrm{LF}} + \phi_{25\text{-}34}^{\mathrm{LF}}$; (ii) dashed line with squares (left axis) shows $\phi_{35\text{-}44}^{\mathrm{LF}} + \phi_{45\text{-}54}^{\mathrm{LF}}$; and (iii) dashed-dotted line with diamonds (right axis) shows $\phi_{55\text{-}64}^{\mathrm{LF}}$.

Figure B.2: Trends in the Age Composition of U.S. Employment, 1950-2015

Notes: Panel A shows the average age of the U.S. employment pool (20-64 years old). The average age of employment is calculated as $\bar{a}^{\mathrm{E}} \equiv \sum_{a \in A} \left(\frac{\underline{a}+\bar{a}}{2}\right) \phi_a^{\mathrm{E}}$, where $\underline{a}$ and $\bar{a}$ are respectively lower and upper bounds of the age group $a \in A$, with $A = \{20\text{-}24, 25\text{-}34, 35\text{-}44, 45\text{-}54, 55\text{-}64\}$, and ϕ_a^{E} is the age-specific employment share (the ratio of employed in the age group a to total employment). Panel B shows employment shares by three age groups: (i) full line with circles (left axis) shows $\phi_{20\text{-}24}^{\mathrm{E}} + \phi_{25\text{-}34}^{\mathrm{E}}$; (ii) dashed line with squares (left axis) shows $\phi_{35\text{-}44}^{\mathrm{E}} + \phi_{45\text{-}54}^{\mathrm{E}}$; and (iii) dashed-dotted line with diamonds (right axis) shows $\phi_{55\text{-}64}^{\mathrm{E}}$.

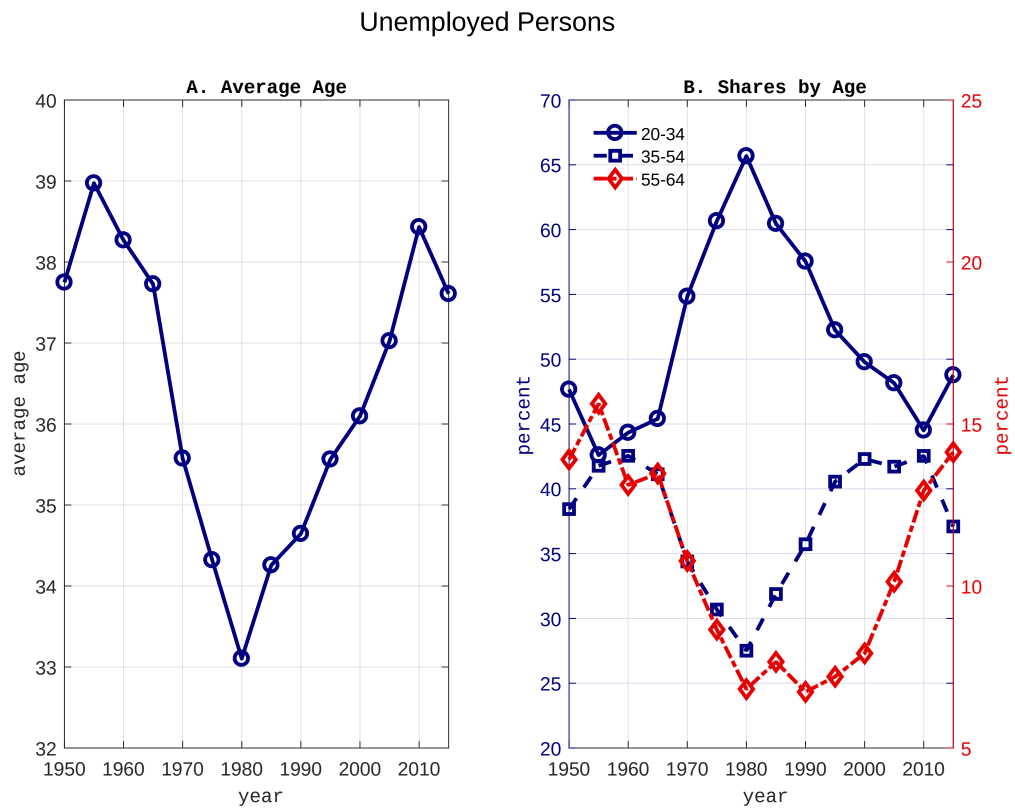

Figure B.3: Trends in the Age Composition of U.S. Unemployment, 1950-2015

Notes: Panel A shows the average age of the U.S. unemployment pool (20-64 years old). The average age of unemployment is calculated as $\bar{a}^{\mathrm{U}} \equiv \sum_{a \in A} \left(\frac{\underline{a} + \overline{a}}{2} \right) \phi_a^{\mathrm{U}}$, where $\underline{a}$ and $\overline{a}$ are respectively lower and upper bounds of the age group $a \in A$, with $A = \{20\text{-}24, 25\text{-}34, 35\text{-}44, 45\text{-}54, 55\text{-}64\}$, and ϕ_a^{U} is the age-specific unemployment share (the ratio of unemployed in the age group a to total unemployment). Panel B shows unemployment shares by three age groups: (i) full line with circles (left axis) shows $\phi_{20\text{-}24}^{\mathrm{U}} + \phi_{25\text{-}34}^{\mathrm{U}}$; (ii) dashed line with squares (left axis) shows $\phi_{35\text{-}44}^{\mathrm{U}} + \phi_{45\text{-}54}^{\mathrm{U}}$; and (iii) dashed-dotted line with diamonds (right axis) shows $\phi_{55\text{-}64}^{\mathrm{U}}$.

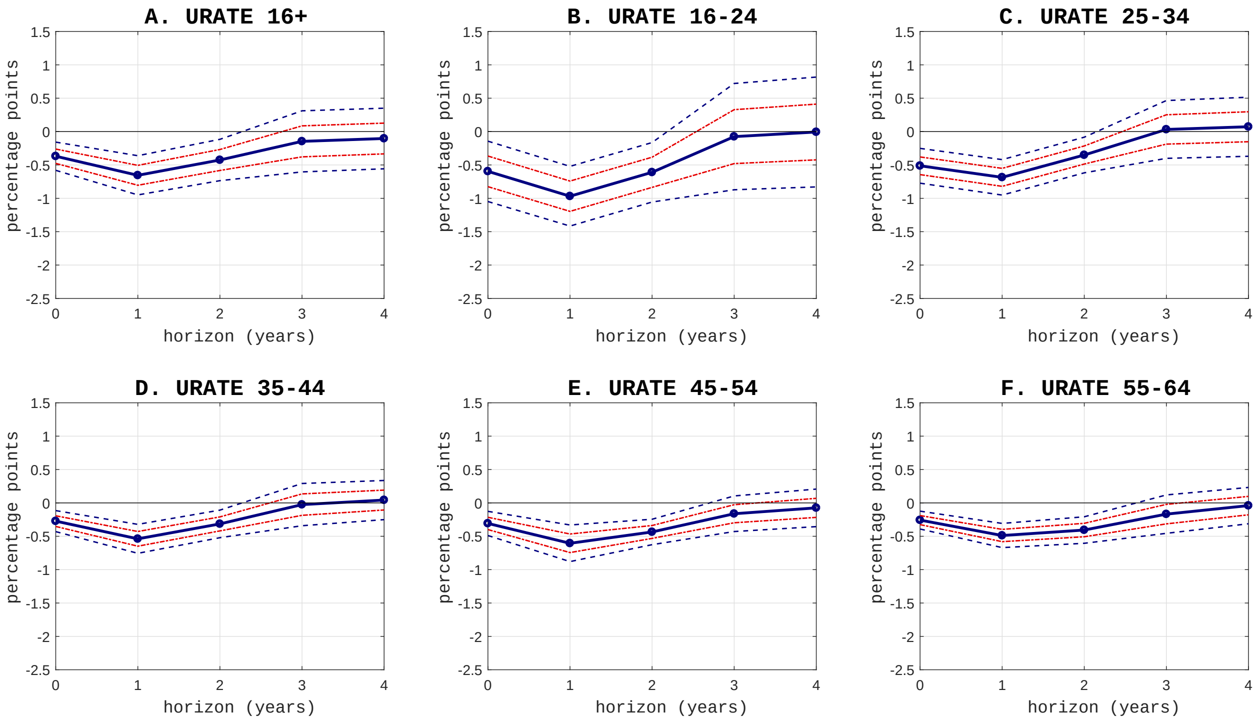

Figure B.4: Unemployment Rate Responses to an Aggregate Tax Cut by Age

Notes: The figure shows the response to a 1 percentage point cut in the aggregate AMTR. Full lines with circles are point estimates; dash-dotted lines are 68 percent confidence bands; dashed lines are 95 percent confidence bands. Both intervals are computed using the Delta-method suggested by Montiel-Olea et al. (2017) with a Newey and West (1987) HAC-robust residual covariance matrix.

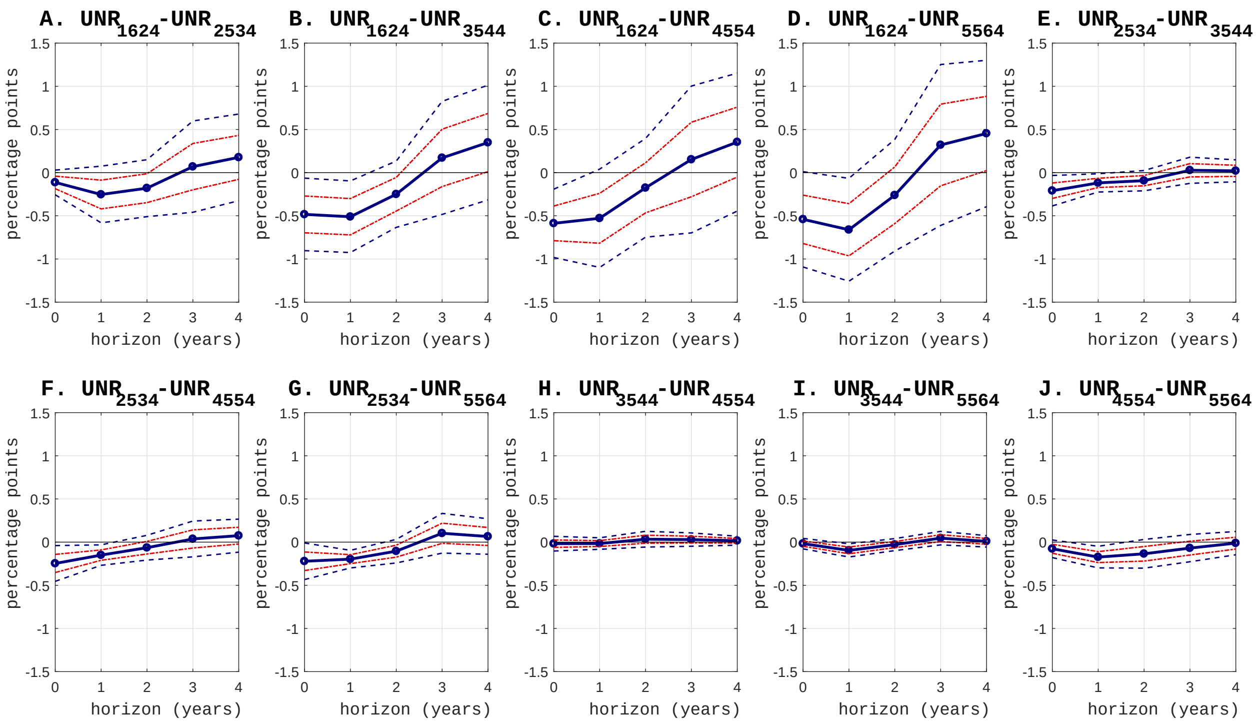

Figure B.5: Age Differences in Unemployment Rate Responses to Age-specific Tax Cuts

Notes: The figure shows age differences in responses to a 1 percentage point cut in age-specific AMTR. Proxy SVAR is estimated with age-specific AMTR and age-specific proxies. Full lines with circles are point estimates; dash-dotted lines are 68 percent confidence bands; dashed lines are 95 percent confidence bands. Both intervals are computed using the Delta-method suggested by Montiel-Olea et al. (2017) with a Newey and West (1987) HAC-robust residual covariance matrix.

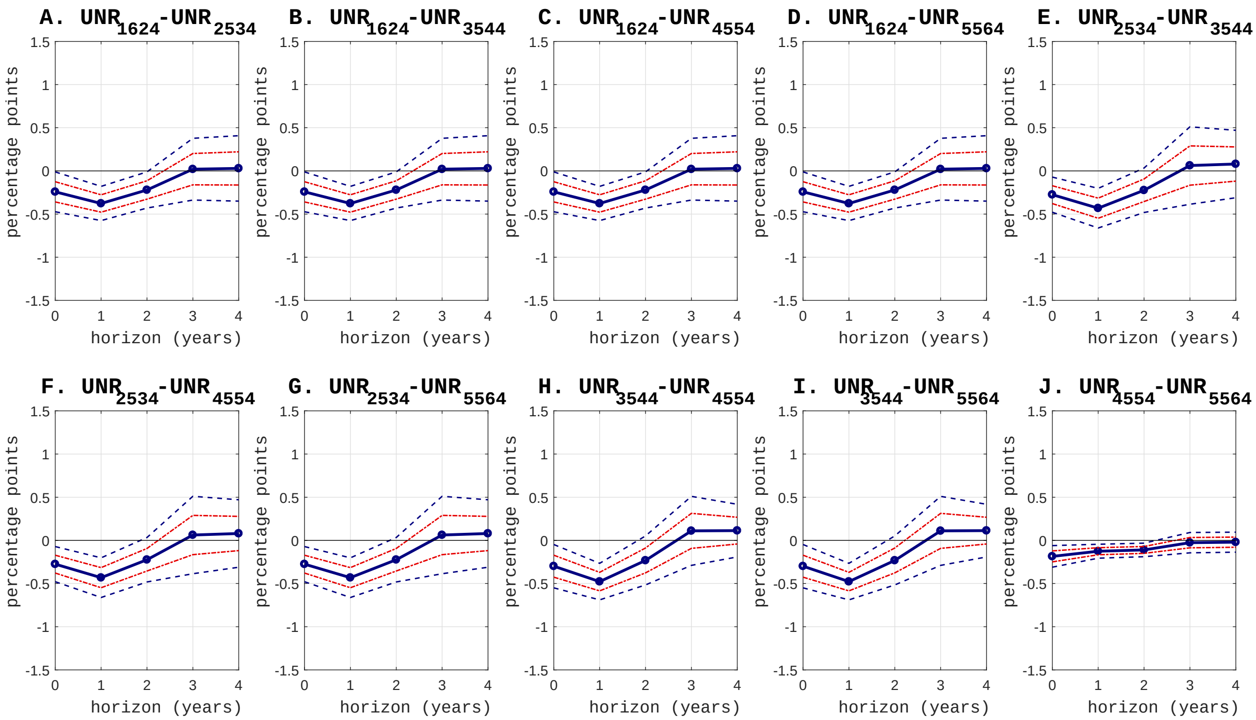

Figure B.6: Age Differences in Unemployment Rate Responses to an Aggregate Tax Cut

Notes: The figure shows age differences in responses to a 1 percentage point cut in the aggregate AMTR. Full lines with circles are point estimates; dash-dotted lines are 68 percent confidence bands; dashed lines are 95 percent confidence bands. Both intervals are computed using the Delta-method suggested by Montiel-Olea et al. (2017) with a Newey and West (1987) HAC-robust residual covariance matrix.

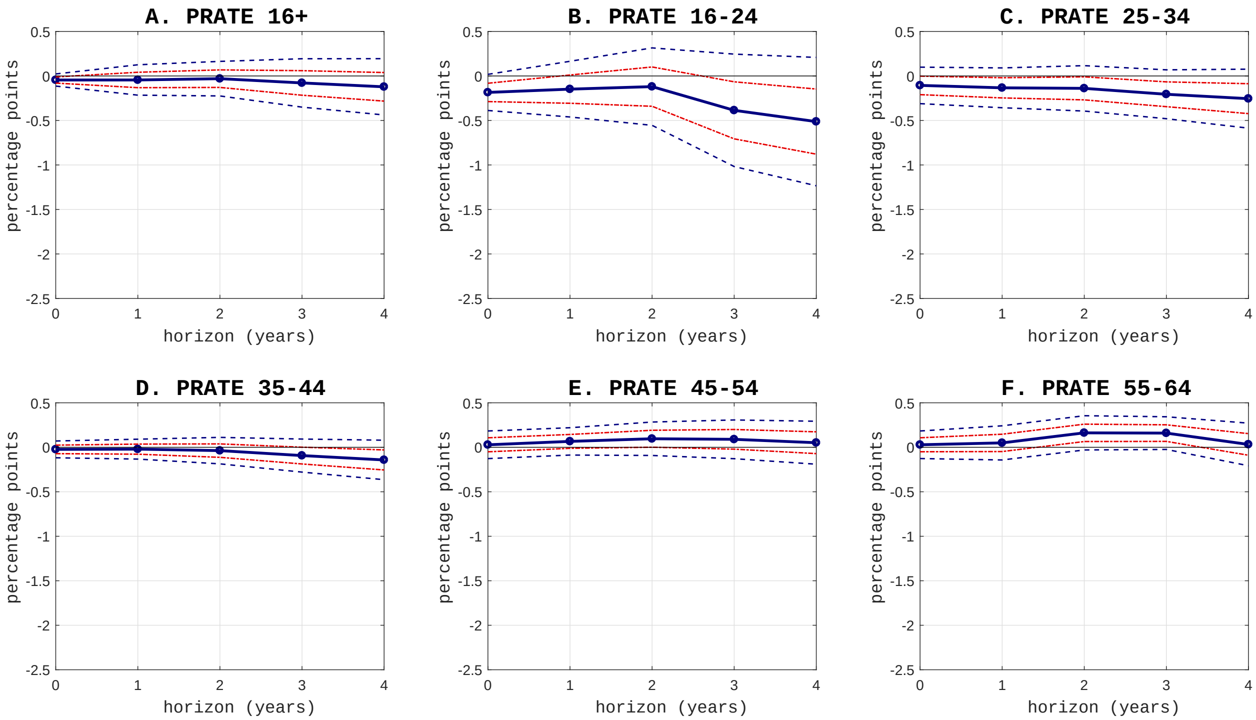

Figure B.7: Participation Rate Responses to an Aggregate Tax Cut by Age

Notes: The figure shows the response to a 1 percentage point cut in the aggregate AMTR. Full lines with circles are point estimates; dash-dotted lines are 68 percent confidence bands; dashed lines are 95 percent confidence bands. Both intervals are computed using the Delta-method suggested by Montiel-Olea et al. (2017) with a Newey and West (1987) HAC-robust residual covariance matrix.