

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

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Abstract

We investigate the consequences of demographic change for the effects of tax cuts in the United States over the post-WWII 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 prime-age workers. Such 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 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 ask the question: How do 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.

We establish the relationship between demographics and tax cuts in the following manner. We document that the responsiveness of unemployment rates to tax shocks largely varies across age groups: the unemployment rate response of the young is nearly twice as large as that of prime-age workers. Documenting these age-specific differences in the responsiveness to tax shocks is the first contribution of the paper. This heterogeneity is the channel through which shifts in the age composition of the U.S. labor force affect the response of the aggregate unemployment rate to tax changes. We then *quantify* the impact of an aging labor force on the propagation of tax shocks. Quantifying these effects is the second contribution of the paper. We argue that the aging of the baby boomers considerably reduces the effects of tax cuts on aggregate unemployment.

Recently, a great deal of attention has been devoted to studying the effects of government purchases and taxes. The policy debates in the aftermath of the Great Recession of 2007-2009 in the United States have led to renewed interest in the effectiveness of countercyclical fiscal policy in stimulating economic activity. Not surprisingly, then, a growing strand of empirical literature has been studying the effects of fiscal policy shocks. We have learned a lot from this body of work. Yet, our understanding of the propagation mechanisms of fiscal policy shocks remains incomplete. The bulk of the literature considers aggregate macroeconomic variables, which is the natural starting point for analyzing the economic forces that shape the aggregate response to fiscal policy shocks.¹ We pursue instead a disaggregated analysis by considering one specific dimension of heterogeneity, that can be measured uncontroversially,

¹See Ramey and Shapiro (1998), House and Shapiro (2006, 2008), Pappa (2009), Romer and Romer (2010), Monacelli et al. (2010), Barro and Redlick (2011), Ramey (2011a,b), Auerbach and Gorodnichenko (2012), Brückner and Pappa (2012), Cloyne (2013), Mertens and Ravn (2013, 2014), Ramey and Zubairy (2014), Nakamura and Steinsson (2014), Acconcia et al. (2014), Mertens (2015), Barnichon and Matthes (2015) for estimates of the effects of government purchases and taxes on macroeconomic aggregates, such as real gross domestic product (GDP), consumption, investment, and unemployment.

that is, age. However, our ultimate goal is to gauge the implications of demographic change for the *aggregate* unemployment response to tax cuts. To date, this paper is the first attempt to tackle such a question.²

Recent work has also studied the implications of demographic change for macroeconomic 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 the bulk of the low-frequency movements in the U.S. unemployment rate since World War II, whereas [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. Early studies have also investigated the effects of demographic change on national saving (see [Auerbach and Kotlikoff, 1989, 1992](#); [Ríos-Rull, 2001](#); [Abel, 2003](#); [Ferrero, 2010](#); [Carvalho et al., 2016](#)), and financing of Social Security (see [Cooley and Soares, 1996](#); [De Nardi et al., 1999](#); [Bohn, 1999](#); [Kotlikoff et al., 2007](#); [McGrattan and Prescott, 2016](#)). In this paper, instead, we investigate if and the extent to which the aging of the baby boomers impacts the effectiveness of tax cuts in reducing 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 \(2009\)](#), [Dyrda et al. \(2012\)](#), and [Jaimovich et al. \(2013\)](#) assess the aggregate implications of age-specific differences in cyclical movements of hours worked.

To empirically estimate the responses of aggregate and age-specific unemployment rates to unanticipated, temporary tax changes, we use 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 (SVARs) to estimate the dynamic responses to a temporary tax cut, as in [Mertens and Ravn \(2013\)](#). We consider average marginal tax rates as we are interested in the transmission mechanism of tax changes that operates through incentive effects on intertemporal substitution rather than disposable income. We establish that the responsiveness of unemployment rates to tax changes largely

²[Anderson et al. \(2015\)](#) document heterogeneous effects of fiscal policy shocks on consumption, based on income levels and age, whereas [Wong \(2015\)](#) studies the implications of demographic change for the response of consumption to monetary policy shocks.

varies across age groups: the unemployment rate response of the young is nearly twice as large as that of prime-age workers. By contrast, we show that the age-specific labor force shares are in fact unresponsive to the (narratively identified) changes in average marginal tax rates. 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 time 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.

Given these observations, a natural conjecture is that the responsiveness of the aggregate U.S. unemployment rate to tax changes depends on the age composition of the labor force. When an economy is characterized by a smaller share of young workers, everything else equal, these should be periods of lesser aggregate responsiveness to tax cuts. We show that this is indeed the case. 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 then a simple quantitative accounting of how the observed demographic trends in the United States impact the effectiveness of tax cuts in reducing aggregate unemployment. We find that the aging of the baby boomers reduces the response of the aggregate U.S. unemployment rate to a tax cut by roughly fifty percent.

The implications for countercyclical fiscal policy are self-evident. In the United States, given the current fertility and mortality rates, the population and so the workforce 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. Policies targeted at labor force participation would then seem the natural candidates for the future of stimulus policies.

The paper is organized as follows. In Section 2, we describe the evolution of population and labor force shares by age group in the United States for the post-war period 1950-2015. In Section 3, we introduce the econometric methodology, discuss identification, and present estimates for the aggregate unemployment and participation rate. In Section 4, we present estimates for unemployment rates by age group, and then investigate the role of demographic change for the aggregate unemployment response to tax cuts. Section 5 concludes.

2 Aging of the Baby Boomers: Stylized Facts

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-World War II baby boom and subsequent baby bust resulted in dramatic shifts in the age composition of the U.S. population. These shifts in turn led to pronounced trends in the *average age* of the population.

In Figure 1, panel A shows the average age of the U.S. civilian noninstitutional population of 20-64 years old for the period 1950-2015. Two facts emerge. First, the U.S. population has been steadily 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 mid-1980s as a result of the sharp increase in birth rates after World War II. This is the so-called “baby boom.” However, in the early-1960s, birth rates started to decline towards levels prior to the baby boom. The consequent baby bust led to the sharp inversion in average age observed in the late-1980s. The U.S. population has been aging since then as a result of the aging of the baby boomers.

Notably, these slow-moving trends in the average age of the population result from the underlying shifts in the age composition of the population induced by the baby boom and the subsequent baby bust. Specifically, the *share* of the 20-34 years old in the overall population has been declining since the mid-1980s, which has then tilted the age composition of the population towards older ages.

To see this, we consider 5 age groups (20-24, 25-34, 35-44, 45-54, and 55-64) and calculate the average age of the population as $\bar{a}^P \equiv \sum_a \left(\frac{a+\bar{a}}{2}\right) \phi_a^P$, where \underline{a} and \bar{a} are the lower and upper bounds of age group a , respectively, and ϕ_a^P is the age-specific population share, that is, the ratio of the population in the age group a to the overall population. In Figure 1, panel B shows the dramatic changes in the age composition of the population observed in the United States since 1950. The population share of the 20-34 years old increased by 10 percentage points (from approximately 35 to 45 percent) over the course of twenty years from 1960 to 1980. Over the same period, the population share of the 35-54 years old has instead declined by approximately the same amount. In addition, the population share of the 55-64 years old has remained approximately constant over the same period, it starts declining in the early-1980s to reach a trough in the mid-1990s, when it sharply reverts to steady growth towards an approximately 22 percent of the overall population in 2015. These sustained changes in the age composition of the population are the key drivers of the aging of the U.S. workforce.

Next we show that these underlying demographic trends in the U.S. population are also

affecting the age composition and so the average age of the U.S. labor force (employed plus unemployed workers of 20-64 years old). In Figure 2, panel A shows that, perhaps not surprisingly, the average age of the labor force mirrors the movements in the average age of the U.S. population. The U.S. labor force has been aging since the mid-1980s. In Figure 2, panel B shows that this aging is indeed driven by the underlying shifts in the age composition of the labor force. Specifically, the share of the 20-34 years old in the labor force increased by more than 10 percentage points (from approximately 35 to 48 percent) over the course of fifteen years from the mid-1960s to early-1980s. Over 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 and reaches a trough of approximately 10 percent in the mid-1990s.

The picture that emerges from these facts is clear. The aging of the baby boomers is in fact changing the age composition of the pool of employed and unemployed workers. To the extent that young, prime-age and old workers feature different labor force attachment, turnover rates, and job search intensities, the aging of the labor force may arguably have important implications for the aggregate labor market response to policy changes. In this paper, we show that is indeed the case.

3 Labor Market Response to Tax Cuts

In this section, we establish new facts on the dynamic response of the U.S. labor market to unanticipated changes in taxes. We focus on changes in average *marginal* tax rates (AMTRs) as opposed to changes in *average* tax rates. Hence, we study the transmission mechanism of tax changes that operates through incentive effects on intertemporal substitution rather than income effects through changes in disposable income. Recently, [Mertens \(2015\)](#) shows that real economic activity indeed responds primarily to changes in marginal rather than average tax rates. Specifically, changes in average marginal tax rates on personal income lead to similar income responses regardless of changes in average tax rates. In addition, changes in average tax rates reflect changes in marginal tax rates as well as changes in tax brackets and tax expenditures (e.g., exemptions, deductions, and credits), which arguably have different effects at the individual and aggregate level. Unanticipated changes in AMTRs instead have a more straightforward interpretation akin to a structural disturbance in our theories.

As in [Barro and Redlick \(2011\)](#), AMTR is the average marginal personal income tax rate weighted by a concept of income that is close to labor income: wages, self-employment,

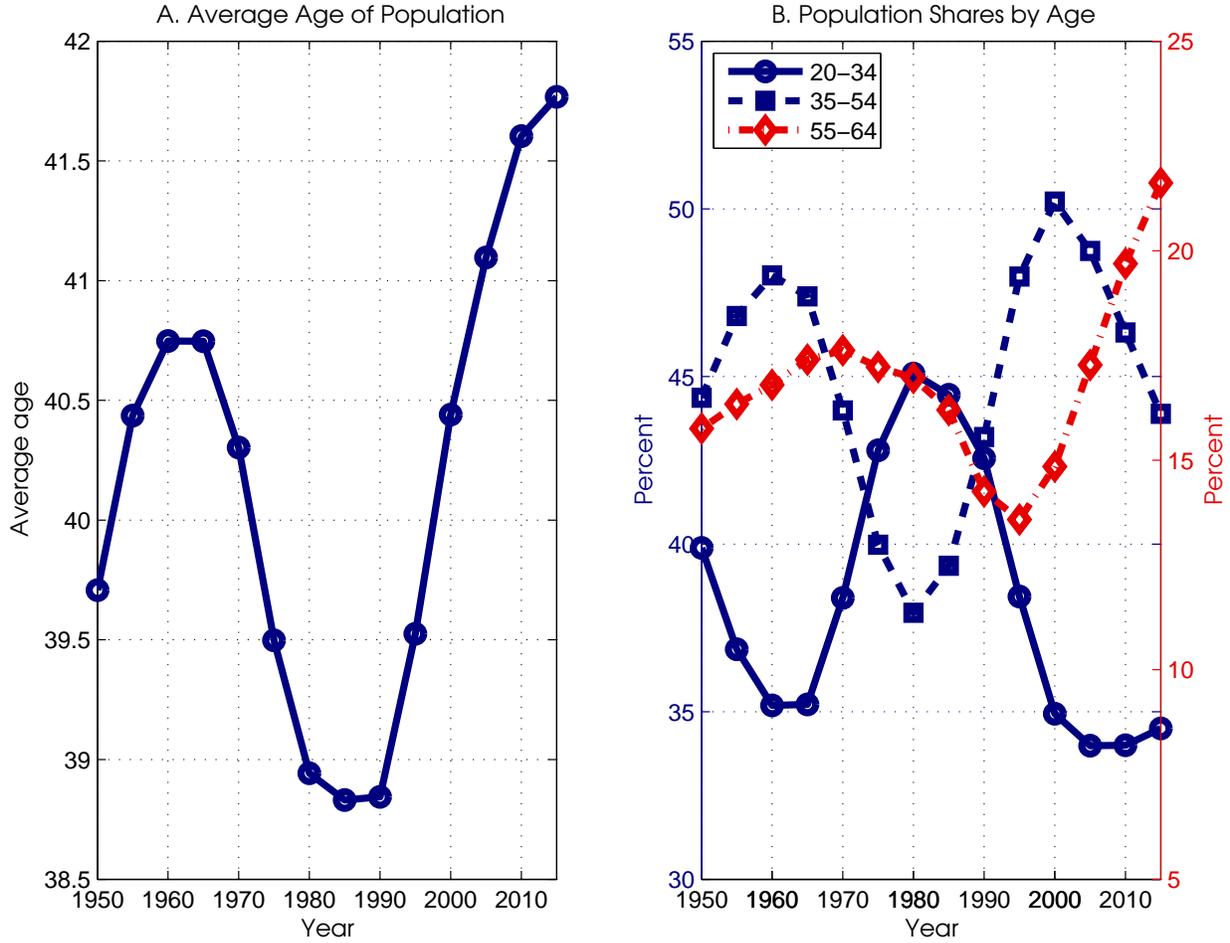


Figure 1: Trends in the Age Composition of the U.S. Population, 1950-2015

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 $\bar{a}^P \equiv \sum_{a \in A} \left(\frac{a + \bar{a}}{2} \right) \phi_a^P$, where \underline{a} and \bar{a} are respectively lower and upper bounds of the age group $a \in A$, with $A = \{20-24, 25-34, 35-44, 45-54, 55-64\}$, 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 $\phi_{20-24}^P + \phi_{25-34}^P$; (ii) dashed line with squares (left axis) shows $\phi_{35-44}^P + \phi_{45-54}^P$; and (iii) dashed-dotted line with diamonds (right axis) shows ϕ_{55-64}^P .

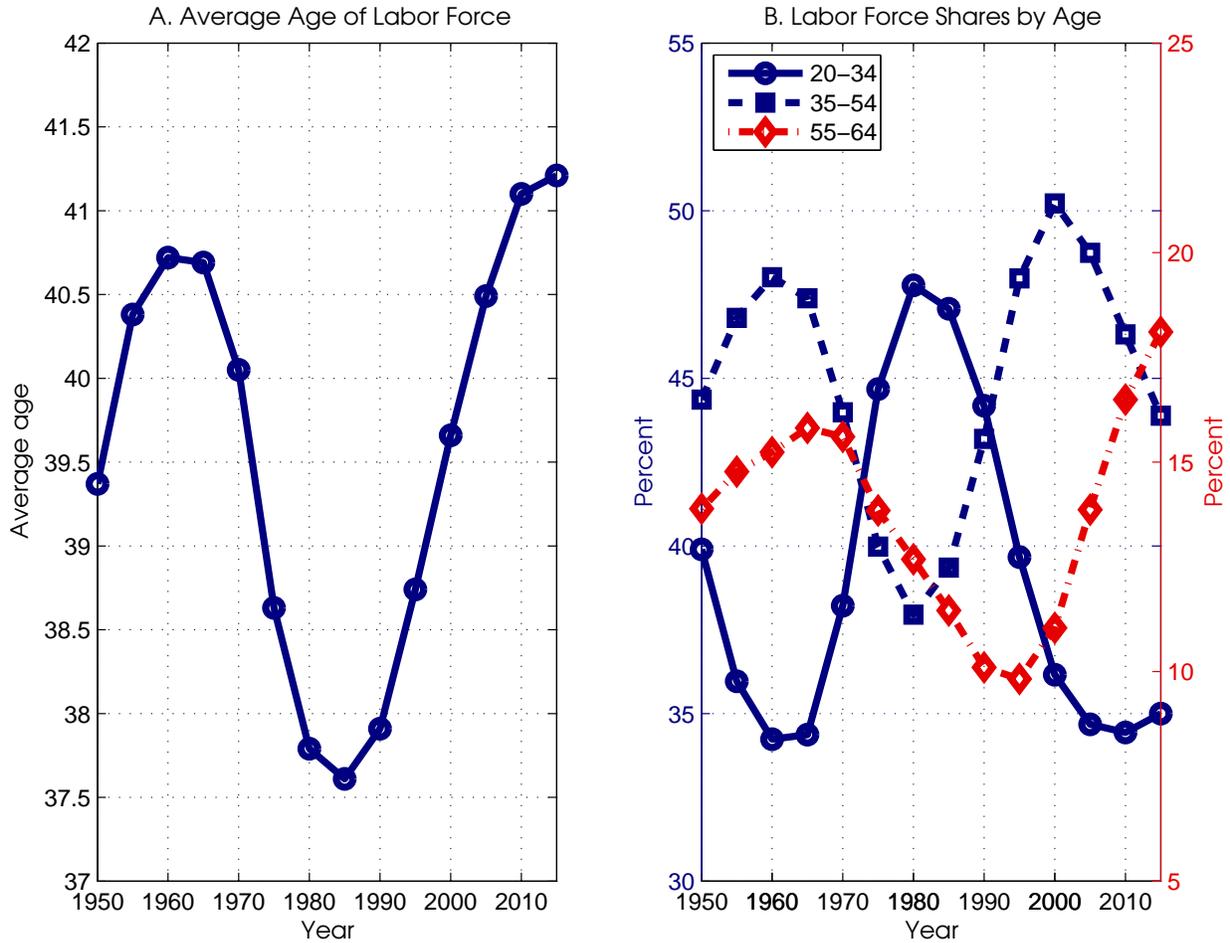


Figure 2: Trends in the Age Composition of the U.S. Labor Force, 1950-2015

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 $\bar{a}^{\text{LF}} \equiv \sum_{a \in A} \left(\frac{a + \bar{a}}{2} \right) \phi_a^{\text{LF}}$, where \underline{a} and \bar{a} are respectively lower and upper bounds of the age group $a \in A$, with $A = \{20-24, 25-34, 35-44, 45-54, 55-64\}$, 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 $\phi_{20-24}^{\text{LF}} + \phi_{25-34}^{\text{LF}}$; (ii) dashed line with squares (left axis) shows $\phi_{35-44}^{\text{LF}} + \phi_{45-54}^{\text{LF}}$; and (iii) dashed-dotted line with diamonds (right axis) shows ϕ_{55-64}^{LF} .

partnership income, and S-corporation income. AMTR consists of two components: federal individual income tax and social security payroll tax (FICA). We then consider two cyclical indicators of the labor market: the unemployment rate (fraction of unemployed workers in the labor force) and the participation rate (fraction of the working-age population in the labor force) at the aggregate and the disaggregated level by age. We focus on the extensive margin of the labor market as it is well-known to be the leading driving force of fluctuations over the business cycle. This is consistent with our focus on unanticipated and temporary tax changes (akin to business cycle shocks). The bulk of the literature considers *aggregate* macroeconomic variables, which is the natural starting point for analyzing the economic forces that shape the aggregate response to tax changes. This focus on aggregate time series is arguably due to the predominance of theories based on the representative household framework. We pursue instead a *disaggregated* analysis by considering one specific dimension of heterogeneity, that can be measured uncontroversially, that is, *age*. Specifically, we investigate whether the effects of tax cuts systematically differ across young, prime-age, and old workers. However, we emphasize that our ultimate goal is to ask whether accounting for the dramatic changes in the age composition of the labor force observed in the United States, provides new insights into the propagation mechanism of tax cuts.

3.1 Identification of Tax Shocks and SVAR Specification

We use structural vector autoregressions (SVARs) to gauge the dynamic effects of changes in AMTRs. SVARs have been extensively used in the macroeconomics literature to evaluate the effects of monetary and fiscal discretionary policy actions as well as other aggregate shocks (e.g., technology, oil price shocks). In our context, we associate a “tax shock” to a VAR innovation to 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 a news about future policy actions (see [Ramey, 2015](#)).

Identification of tax shocks. Based on [Mertens and Ravn \(2013, 2014\)](#), identification of the structural tax shocks is obtained by the means of SVARs and the use of a proxy for exogenous variation in tax rates as an external instrument (“proxy SVAR”). We use the time series of exogenous changes in *individual income* tax liabilities constructed by [Mertens and Ravn \(2013\)](#) as the designed proxy. These narratively identified, tax liabilities shocks are then used as an instrument to sort out the contemporaneous causal relationship between AMTRs and labor market variables in an annual sample of fifty-seven years, 1950-2006. [Mertens](#)

and Ravn (2013) provide a narrative account of legislated federal individual income tax liability changes in the United States for a quarterly sample covering 1950:Q1-2006:Q4. Their approach builds on the seminal work by Romer and Romer (2009, 2010). That is, 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 current state of the economy (e.g., the business cycle) or inherited budget deficits concerns. Notably, Mertens and Ravn decompose the total tax liabilities changes recorded by Romer and Romer (2009) into two main subcomponents: individual income tax liabilities (including employment taxes) and corporate income tax liabilities changes. An additional concern is that legislated tax changes are often implemented with a considerable lag, which arguably hints at the presence of anticipation effects. Mertens and Ravn (2012) indeed provide evidence of aggregate effects of legislated tax changes prior to their implementation. We instead focus on unanticipated tax changes and so use observations on individual income tax liability changes legislated and implemented within the year to avoid anticipation effects, as in Mertens and Ravn (2013). As a result, the time series of individual income tax liabilities changes used for identification consists of 13 quarterly observations. Most of these changes were legislated as permanent. Moreover, we scale these tax liability changes by the personal income tax base in the previous quarter.³ This allows us to convert tax liability changes into the corresponding changes in the average tax rates on individual income. Henceforth, we refer to these scaled changes in individual income tax liabilities as “narrative shocks.”

Figure 3 shows AMTRs and the resulting narrative shocks (after subtracting the mean of non-zero observations). Panel A shows a marked upward trend in AMTRs from 1950 to the early-1980s. Specifically, the AMTR increased by nearly 6 percentage points (from 20 to 25.9 percent) from 1950 to 1952, it then fluctuates in the 23-27 percent range over the course of approximately twenty years from the early-1950s to the early-1970s. In the 1970s, AMTRs sharply rise from 25 percent towards the post-war peak of 38 percent in the early-1980s. Such an acceleration was primarily due to bracket creep effects induced by rising inflation (the so-called “Great Inflation” of the 1970s). After the 1980s, the sustained raises in the social security payroll tax have been almost entirely offset by reductions in federal individual income taxes, which have remained in the 20-25 percent range since then. Beyond these long-run trends, the time series of AMTRs also points to substantial year-to-year variation over the post-WWII period. The raw standard deviation of the first-difference

³Personal income tax base is defined as personal income less government transfers plus contributions for government social insurance. See Appendix A for data sources.

in AMTRs is 1.3 percentage points for 1950-2006. Most of this year-to-year variation is driven by changes in federal individual income taxes. Note also that AMTRs do not include state-level taxes. However, the amount of short-run variation in state-level marginal tax rates is rather small (see [Barro and Redlick, 2011](#)). These year-to-year changes in federal individual income taxes in turn reflect well-known legislative actions. For instance, the Revenue Act of 1950 raised individual tax rates to meet the financing needs for defense expenditure due to the Korean War; the tax cuts in the Revenue Act of 1964; the individual income surtaxes in the Revenue and Expenditure Control Act of 1968 during the Vietnam War; the tax cuts in the Economic Recovery Tax Act of 1981 and the Tax Reform Act of 1986; the tax increases in the Omnibus Budget Reconciliation Act of 1990 and 1993; and the tax cuts in the Economic Growth and Tax Relief Reconciliation Act of 2001 (EGTRRA). We refer the reader to [Yang \(2007\)](#) for a detailed chronology of major tax events in the United States. Hence, the full post-WWII history of U.S. federal income tax policy includes several large increases and decreases in average marginal tax rates, which arguably provides valuable identifying variation. Yet, the vast majority of the observed legislated changes in AMTRs result from policy actions aimed at offsetting cyclical downturns. This poses well-known challenges for the identification of the causal effects of temporary tax changes on economic activity. Panel B shows three major exogenous changes in individual income tax rates. First, the Revenue Act of 1964 enacted by president Lyndon Johnson on February 26, 1964, substantially reduced statutory marginal tax rates across the board. According to the time series of narrative shocks, this specific legislation cut average personal income tax rates by 1.4 percentage points. Second, the Revenue Act of 1978 enacted by president James Carter on November 6, 1978, lowered individual tax rates. It also widened and reduced the number of tax brackets such that taxpayers would not be pushed to a higher tax rate due to raising inflation. This legislation cut average personal income tax rates by 0.8 percentage points. Third, the Jobs and Growth Tax Relief Reconciliation Act of 2003 (JGTRRA) enacted by president George Bush on May 28, 2003, reduced marginal tax rates on individual income, capital gains, and dividends. Nearly all of the cuts in JGTRRA were temporary and set to expire after 2010. This legislation cut average personal income tax rates by approximately 1 percentage point. Furthermore, the Tax Relief, Unemployment Insurance Reauthorization, and Job Creation Act of 2010 enacted by president Barack Obama on December 17, 2010, extended the tax cuts in JGTRRA for two years.

SVAR specification. First introduced by [Sims \(1980\)](#), SVARs have been widely used to study the joint dynamic behavior of multiple aggregate time series by allowing for general

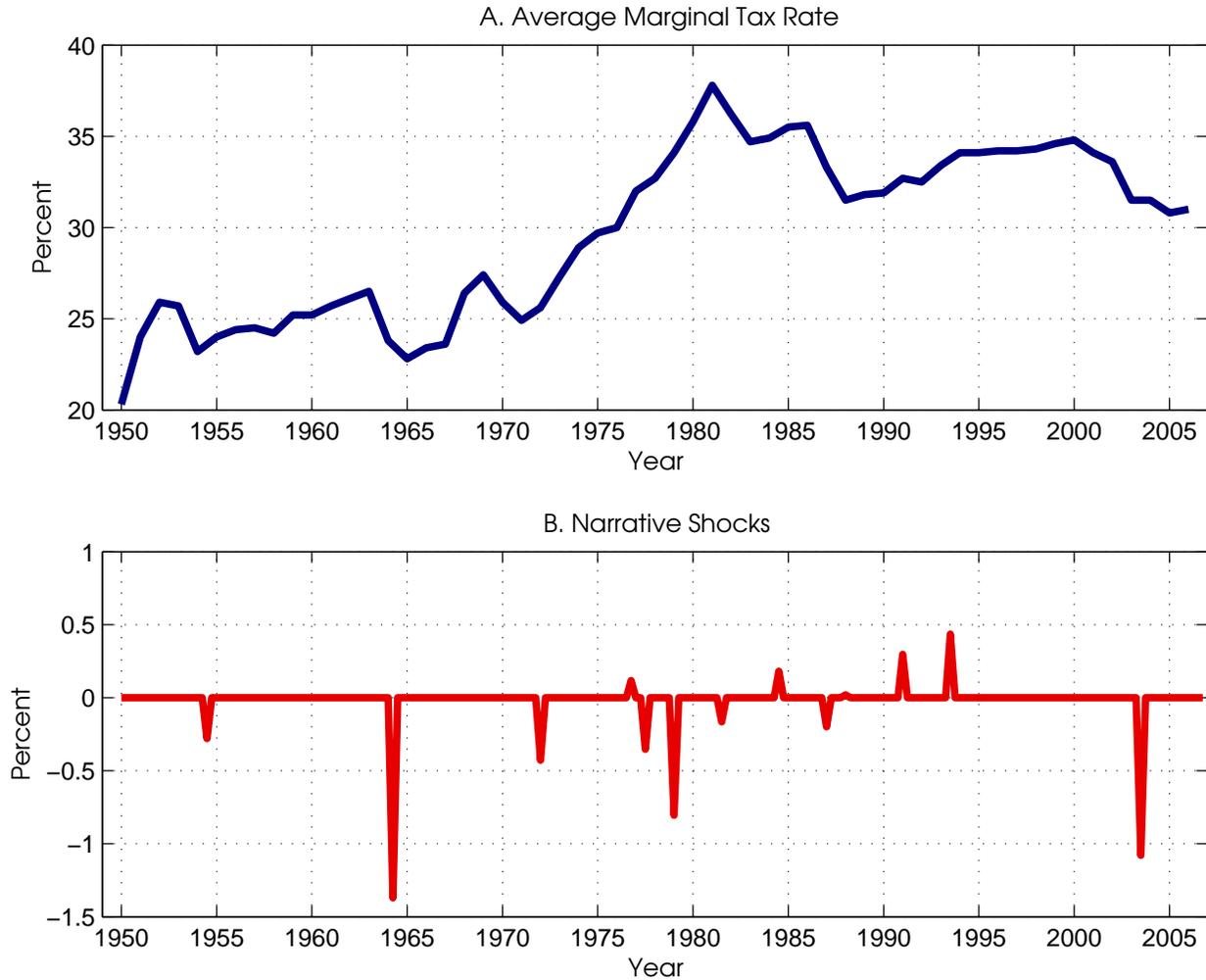


Figure 3: Average Marginal Tax Rates and Narrative Shocks, 1950-2006

Notes: Panel A shows the average marginal tax rate (AMTR) constructed by [Barro and Redlick \(2011\)](#). AMTR is the average marginal personal income tax rate weighted by a concept of income that is close to labor income: wages, self-employment, partnership income, and S-corporation income. AMTR consists of two components: federal individual income tax and social security payroll tax (FICA). Panel B shows the exogenous changes in individual income tax liabilities divided by the personal income tax base in the previous quarter (personal income less government transfers plus contributions for government social insurance), as constructed by [Mertens and Ravn \(2013\)](#).

feedback mechanisms. Specifically, SVARs 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 economic 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, SVARs also identify the expected future 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 behavioral response to discretionary tax changes.

We consider a sample of annual observations for the period 1950-2006. Our estimates of the effects of shocks to AMTRs on the U.S. labor market are based on a SVAR with five variables, $\mathbf{Y}_t \equiv [\text{AMTR}_t, \ln(\text{PITB}_t), \ln(G_t), \mathbf{X}_t, \ln(\text{DEBT}_t)]'$, (the subscript “ ’ ” denotes the transpose operator), where (i) AMTR_t is the average marginal personal income tax rate, as constructed by [Barro and Redlick \(2011\)](#); (ii) PITB_t is the personal income tax base in real per capita terms; (iii) G_t is government purchases of final goods in real per capita terms; (iv) \mathbf{X}_t is the specific labor market variable of interest. That is, aggregate unemployment and participation rates in [Section 3.2](#), job-separation and job-finding rates, as constructed by Robert Shimer (see [Shimer, 2012](#), for details), in [Section 3.3](#), and unemployment rates by age in [Section 4](#); and (v) DEBT_t is federal debt in real per capita terms. The baseline reduced-form VAR specification is

$$\begin{bmatrix} \text{AMTR}_t \\ \ln(\text{PITB}_t) \\ \ln(G_t) \\ \mathbf{X}_t \\ \ln(\text{DEBT}_t) \end{bmatrix} = d_t + B(L) \begin{bmatrix} \text{AMTR}_{t-1} \\ \ln(\text{PITB}_{t-1}) \\ \ln(G_t) \\ \mathbf{X}_t \\ \ln(\text{DEBT}_t) \end{bmatrix} + \begin{bmatrix} e_t^{\text{AMTR}} \\ e_t^{\text{PITB}} \\ e_t^G \\ e_t^{\mathbf{X}} \\ e_t^{\text{DEBT}} \end{bmatrix}, \quad (1)$$

where d_t contains deterministic terms and $B(L)$ is a lag polynomial of finite order $p - 1$. The lag length in the VAR is set to $p = 2$. The vector $e_t \equiv [e_t^{\text{AMTR}}, e_t^{\text{PITB}}, e_t^G, e_t^{\mathbf{X}}, e_t^{\text{DEBT}}]'$ contains the reduced-form VAR innovations.

Government debt is an important variable to include in the VAR specification: given the government’s budget constraint, any change in tax rates must eventually lead to adjustments in other fiscal instruments, as such we deem appropriate to explicitly allow for the feedback from debt to taxes and spending.⁴ Furthermore, since tax changes are often motivated

⁴[Christ \(1968\)](#) and [Sims \(1998\)](#) warn against policy analysis that fails to keep track of the implications of

by concerns about government deficits and so 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.

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 $\epsilon_t \equiv [\epsilon_t^{\text{AMTR}}, \epsilon_t^{\text{PITB}}, \epsilon_t^G, \epsilon_t^{\mathbf{X}}, \epsilon_t^{\text{DEBT}}]'$, such that: (i) $\mathbb{E}[\epsilon_t] = 0$, (ii) $\mathbb{E}[\epsilon_t \epsilon_t'] = \Sigma_\epsilon$ is a diagonal matrix (we further impose $\Sigma_\epsilon \equiv I$, where I is the identity matrix), and (iii) $\mathbb{E}[\epsilon_t \epsilon_{t-j}'] = 0$ 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, $\mathbb{Y}_t \equiv [\mathbf{Y}'_{t-1}, \dots, \mathbf{Y}'_{t-p}]'$. Hence, we posit that $e_t = \mathcal{H}\epsilon_t$, where \mathcal{H} is a matrix of parameters that determines the contemporaneous 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 $i = 1, \dots, \dim(\mathbf{Y}_t)$, that determine the contemporaneous response of the observables, \mathbf{Y}_t , to the shock to AMTRs, ϵ_t^{AMTR} . Identification of $\mathcal{H}^{i,1}$ is achieved by imposing the same identifying restrictions in [Mertens and Ravn \(2013, 2014\)](#) 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 $\mathbb{E}[m_t \epsilon_t^{\text{AMTR}}] \neq 0$ and $\mathbb{E}[m_t \epsilon_t^i] = 0$ for $i \geq 2$ (the subscript “ 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 instead the proxy to be contemporaneously uncorrelated with all other structural shocks. Based on the proxy SVAR approach of [Mertens and Ravn \(2013, 2014\)](#), our proxy variable is the series of narrative shocks depicted in panel B of [Figure 3](#). Once the contemporaneous (or impact response) parameters of interest are identified and estimated, the effects of an unanticipated exogenous tax shock in subsequent years can be traced out using the estimated system in (1). The resulting impulse response functions (IRFs) measure the expected dynamic adjustment of all the endogenous variables to the initial shock to the average marginal tax rate. IRFs allow for general feedback effects and so convey insight into the propagation mechanism of tax cuts. All impulse responses are for a 1 percentage point cut in AMTR and we show results for a forecast horizon of 5 years.

the government budget constraint, and [Burnside et al. \(2004\)](#) and [Ramey \(2011b\)](#) argue that the effects of shocks to government purchases may differ depending on the endogenous response of other fiscal instruments.

3.2 Aggregate Response to Tax Cuts

We now turn to study the dynamic response of the U.S. labor market to tax cuts. Specifically, we consider aggregate variables that are key cyclical indicators of economic slack in the labor market: the aggregate U.S. unemployment rate and participation rate. Hence, we focus on movements of workers in and out of employment, the “extensive margin” of the labor market, that is well known to be the leading driving force of fluctuations in total hours worked over the business cycle (see [Lilien and Hall, 1986](#); [Rogerson and Shimer, 2011](#)). This is indeed consistent with the ultimate goal of this paper of understanding the aggregate effects of unanticipated and temporary tax shocks, that are akin to the standard business cycle shocks we study in theories of economic fluctuations (e.g., technology, oil price shocks).

To interpret the main empirical findings of this section, we will make use of the following decomposition of the employment to population ratio:

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

Such a 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 dynamic response of either the unemployment rate or participation rate, or both. Next we show that unemployment is indeed quite responsive to tax cuts, whereas participation is not.

Figure 4 shows the dynamic response of the aggregate unemployment rate, for workers of 16 years and older, to a 1 percentage point cut in AMTR. The estimates point to large aggregate effects of tax changes. Notably, the peak response, that occurs 3 years after the initial shock, implies that a 1 percentage point cut in AMTRs leads to an approximately 0.7 percentage points decrease in the aggregate unemployment rate. Importantly, we note that historically a 1 percentage point cut in AMTR is not an unusual event as the standard deviation of changes in AMTRs is 1.3 percentage points for the post-war period 1950-2006. These findings point to a highly statistically significant and quantitatively large effects of tax cuts on the aggregate U.S. unemployment rate. 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 on personal income arguably have larger effects than changes in average tax rates as they operate through incentive effects on intertemporal substitution. Furthermore, we find that tax cuts are long-lasting. The estimated dynamic response of the AMTR to the tax shock is highly persistent. Specifically, AMTRs remain persistently below average up to 5 years after the shock. This high persistence in the adjustment dynamics of the AMTRs contrasts with the relatively fast mean reversion observed for average personal income tax rates, as estimated by [Mertens and Ravn \(2013\)](#), but it is in line with [Mertens and Ravn \(2013\)](#) when they estimate the response of real GDP per capita to tax cuts using the same measure of AMTRs we consider here and, more recently, [Mertens \(2015\)](#) for shocks to AMTRs across different percentiles of the U.S. income distribution.

Figure 5 shows the dynamic response of the aggregate participation rate, for workers of 16 years and older, to an equally-sized 1 percentage point cut in AMTRs. In contrast with the results for the aggregate unemployment rate, the response of the participation rate is both statistically and economically insignificant. Thus, these results indicate that the aggregate response of the employment to population ratio is in fact the mirror image of the response of the aggregate unemployment rate. Therefore, unemployment, as opposed to participation, is the key margin for understanding the aggregate response of the U.S. labor market to the narrative tax shocks. This finding is perhaps not surprising since the participation rate has displayed pronounced low-frequency movements over the post-war period, that are arguably driven by long-run demographic trends which are hardly affected given the magnitude of the shocks observed in the sample period 1950-2006. However, one cannot a priori dismiss the hypothesis that larger shocks to AMTRs could generate a substantially different response in participation. In that scenario, the main concern would be whether linear SVARs remain reliable in recovering the true population response to such large shocks.

3.3 Inspecting the Propagation Mechanism of Tax Cuts

What is the propagation mechanism of tax shocks? To answer this question, we next focus on the reduced-form implications of the typical DMP model of equilibrium unemployment (see [Diamond, 1982](#); [Mortensen, 1982](#); [Pissarides, 1985](#)). In this class of models, changes in unemployment rates are driven by the fraction of employed workers who lost jobs in the previous period minus the unemployed workers who found jobs:

$$u_{t+1} - u_t = s_t e_t - f_t u_t, \quad (2)$$

where the variables u_t and $e_t = 1 - u_t$ are unemployment and employment stocks, respectively, and s_t and f_t are job-separation and job-finding rates, respectively. Thus, equation (2) identifies the job-separation rate (the “separation margin”) and the job-finding rate (the “hiring margin”) as key driving forces of changes in the aggregate unemployment rate, which are then also responsible for the response of the aggregate unemployment rate to shocks.

In DMP models of endogenous job separations (see [Mortensen and Pissarides, 1994](#); [Ramey et al., 2000](#); [Fujita and Ramey, 2012](#)), the flow rates s_t and f_t are jointly determined as equilibrium objects. Yet, we can infer s_t and f_t from actual data under arguably minimal assumptions. Next, we aim at decomposing the relative contribution of separation- versus hiring-driven effects in shaping the aggregate unemployment rate response to tax cuts.

Hence, we now turn to the estimated dynamic responses to narrative tax shocks of the two flow rates: s_t and f_t . Based on publicly available data on unemployment and employment from the Current Population Survey (CPS), time series for s_t and f_t are easily constructed (see [Shimer, 2012](#)).⁵ Figure 6 shows the responses of such constructed series to a 1 percentage point cut in AMTRs. In panel A, the job-separation rate drops by -0.14 percentage points at the trough of the response, whereas, in panel B, the job-finding rate raises by approximately 3 percentage points at the peak of the response. We conclude, then, that both responses are qualitatively consistent with the unemployment rate response in Figure 4, and in accord with the equilibrium reduced-form of the typical DMP model in equation (2).

However, to quantify the relative contribution of separation and hiring margin, we need to derive a decomposition of the unemployment rate response to tax shocks that compares the contribution of job-separation and job-finding rates on an equal footing. To this aim, we proceed in two steps.

First, we rely on a theoretical approximation argument, that hinges on the irrelevance of turnover (or adjustment) dynamics for empirically relevant values of s_t and f_t . In the absence of any type of disturbance, the unemployment rate in (2) converges to the theoretical steady-state value $u_t^{ss} \equiv s_t / (s_t + f_t)$, which only depends on contemporaneous values of job-separation and job-finding rates. [Hall \(2005\)](#) and [Shimer \(2012\)](#) show that, at the quarterly frequency, such steady-state approximation generates values that are nearly indistinguishable

⁵Job-separation and job-finding rates are constructed under two assumptions: (1) workers do not transit in and out of the labor force; and (2) workers are homogeneous with respect to job-finding and job-separation probabilities. We refer the reader to [Shimer \(2012\)](#) for further details.

from the actual unemployment rates observed in U.S. data: that is, $u_t^{\text{ss}} \simeq u_t$ at the quarterly frequency (and thus at lower frequencies as well). This happens because, in the data, $s_t + f_t$ is typically close to 0.5 on a monthly basis, such that the half-life of a deviation from the steady-state unemployment rate is approximately one month. In our sample, monthly job-separation and job-finding rates are 3.4 and 45.3 percent on average, respectively. Figure B.2 in Appendix B confirms that u_t^{ss} is indeed a strikingly good approximation of the actual U.S. unemployment rate for the post-war period 1950-2006.

Second, based on [Elsby et al. \(2009\)](#), [Fujita and Ramey \(2009\)](#), and [Pissarides \(2009\)](#), we decompose the changes in the (steady-state approximation of) actual unemployment rates into the contribution due to changes in the job-separation rate and the contribution due to changes in the job-finding rate:

$$du_t^{\text{ss}} \approx \bar{u}^{\text{ss}} (1 - \bar{u}^{\text{ss}}) \frac{ds_t}{\bar{s}} - \bar{u}^{\text{ss}} (1 - \bar{u}^{\text{ss}}) \frac{df_t}{\bar{f}}, \quad (3)$$

where $dx_t = x_t - \bar{x}$ indicates deviations of the generic variable x_t from its sample average \bar{x} , and $\bar{u}^{\text{ss}} \equiv \bar{s} / (\bar{s} + \bar{f})$, where \bar{s} and \bar{f} are sample averages of job-separation and job-finding rates, respectively. Equation (3) provides an additive decomposition in which the contributions of job-separation and job-finding rates are comparable on an equal footing with respect to their impact on the observed changes in the unemployment rate. Note that equation (3) holds as equality only for infinitesimal changes. For discrete changes, instead, it is only an approximation. However, [Fujita and Ramey \(2009\)](#)'s regression-based estimation of the decomposition in (3) verifies that *unconditionally* it works well for discrete changes.

We next show that such decomposition works well also for the *conditional* response of the U.S. unemployment rate to narrative tax shocks. Specifically, the counterfactual response implied by equation (3) is

$$\widehat{du}_h^{\text{ss}} \equiv \underbrace{\bar{u}^{\text{ss}} (1 - \bar{u}^{\text{ss}}) \frac{\widehat{ds}_h}{\bar{s}}}_{\widehat{du}_h^{\text{jsr}}} - \underbrace{\bar{u}^{\text{ss}} (1 - \bar{u}^{\text{ss}}) \frac{\widehat{df}_h}{\bar{f}}}_{\widehat{du}_h^{\text{jfr}}}, \quad (4)$$

where h is the number of years after the shock and \widehat{ds}_h and \widehat{df}_h are the estimated responses of job-separation and job-finding rates, respectively, as shown in Figure 6.

In Figure 7, panel A shows that the counterfactual response of the unemployment rate under the steady-state approximation, $\widehat{du}_h^{\text{ss}}$, (dashed line with diamonds), is remarkably close to the estimated response of the actual U.S. unemployment rate (full line with circles).

Thus, at the annual frequency, turnover dynamics is in fact negligible for understanding the aggregate response of the actual U.S. unemployment rate to narrative tax shocks. This novel empirical finding bears important implications for theoretical modelling. To the extent that we are interested in the year-to-year dynamic response to “small” tax shocks, theories based on the flow approach to labor markets can safely abstract from adjustment dynamics as steady-state comparisons capture the bulk of the observed aggregate effects of tax cuts. This irrelevance of turnover dynamics for studying the effects of tax cuts can be explained as follows. First, the U.S. labor market is well-known to be extremely fluid; month-to-month worker flows are enormous. In the United States, over the period 1996-2003, approximately 15 million workers changed their labor market status from one month to the next (see Fallick and Fleischman, 2004; Davis et al., 2006). These large workers’ flows translate then into the relatively high, monthly job-separation and job-finding rates observed at the aggregate level, which are in turn responsible for the extremely fast adjustment dynamics featured by the aggregate U.S. unemployment rate. Second, the tax shocks we identified in the data are, on the contrary, extremely persistent. As shown in panel A of Figure 4, the initial 1 percentage point cut in the AMTR persists for nearly 5 years. In a nutshell, unanticipated changes in AMTRs can be viewed as nearly permanent from the perspective of the average worker in the labor force.

Table 1: Separation- versus Hiring-driven Tax Effects

h (years after shock):	1	2	3	4	5
$\widehat{du}_h^{\text{jfr}}$ as % of $\widehat{du}_h^{\text{ss}}$	0.58	0.40	0.36	0.35	0.42
$\widehat{du}_h^{\text{jfr}}$ as % of $\widehat{du}_h^{\text{ss}}$	0.42	0.60	0.64	0.65	0.58

Notes: See equation (4) for definitions of $\widehat{du}_h^{\text{ss}}$, $\widehat{du}_h^{\text{jfr}}$, and $\widehat{du}_h^{\text{jfr}}$.

In Table 1, we use the decomposition in equation (4) to quantify the relative contribution of job-separation and job-finding rates to the response of the actual U.S. unemployment rate to tax shocks. The results show that the job-separation rate accounts for approximately 60 percent of the overall unemployment rate response in the first year after the shock, whereas the split between job-separation and job-finding rates is inverted from the second year after the shock onward. These results indicate that to fully account for the effects of tax shocks, a successful theory has to reproduce the joint dynamic behavior of job-separation and job-

finding rates. We note that these novel empirical findings complement those in early studies on the relative importance of separation and hiring for unemployment fluctuations over the U.S. business cycle (see [Davis et al., 2006](#); [Fujita and Ramey, 2009](#); [Elsby et al., 2009](#)). In this regard, we emphasize that the results in [Table 1](#) derive from the dynamic response of the U.S. unemployment rate *conditional* on a specific, narratively identified shock to AMTRs. Since shocks to AMTRs are identified as orthogonal to business cycle shocks, the decomposition in [Table 1](#) provides additional, independent evidence on the propagation mechanism of shocks at work in the U.S. labor market.

4 Demographics and Aggregate Response to Tax Cuts

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 rates to tax cuts vary by age. In doing so, it is imperative to keep in mind that the effects of a shock to AMTRs on the age-specific unemployment rates incorporate general equilibrium 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. Such a line of reasoning suggests that the SVAR estimates will recover the unemployment response of the average worker in a specific age group, after all the equilibrium feedback effects have played out.

Ultimately, we are interested in decomposing the response of the aggregate unemployment rate in [Figure 4](#) into the relative contribution of each age group. This will in turn allow us to quantify the relative importance of the young, prime-age, and old workers in the labor force in shaping the aggregate response of the U.S. unemployment rate to tax cuts.

4.1 Unemployment Response by Age

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

$$\frac{\text{unemployment}}{\text{labor force}} = \sum_{a \in \mathcal{A}} \underbrace{\frac{\text{labor force}_a}{\text{labor force}}}_{\text{age-specific labor force share}} \times \underbrace{\frac{\text{unemployment}_a}{\text{labor force}_a}}_{\text{age-specific unemployment rate}}, \quad (5)$$

where “ a ” indicates an age group in the list $\mathcal{A} = \{16-19, 20-24, 25-34, 35-44, 45-54, 55+\}$, 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 (5) 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.

In order to disentangle the relative contribution of age-specific labor force shares from that of age-specific unemployment rates, we construct a counterfactual series of the aggregate unemployment rate, u_t^{FLFS} , in which age-specific labor force shares are fixed at their sample averages, $\bar{\phi}_a^{\text{LF}}$, for 1950-2006, whereas we let age-specific unemployment rates, $u_{a,t}$, vary over time:

$$u_t^{\text{FLFS}} \equiv \sum_{a \in \mathcal{A}} \bar{\phi}_a^{\text{LF}} \times u_{a,t}, \quad (6)$$

where $\sum_{a \in \mathcal{A}} \bar{\phi}_a^{\text{LF}} = 1$. We then re-estimate the proxy SVAR by replacing the actual U.S. unemployment rate with the counterfactual unemployment rate with fixed labor force shares, u_t^{FLFS} , in (6). In Figure 7, panel B 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 U.S. unemployment rate (full line with circles). Thus, we conclude that age-specific unemployment rates are indeed quite responsive to tax cuts, whereas age-specific labor force shares are not. This observation corroborates the empirical finding we discussed earlier in this paper that labor market participation, at the aggregate level, seems to be unresponsive to the exogenous changes in AMTRs we identified in the data. As argued in Section 2, 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. Furthermore, workforce composition is largely pre-determined by fertility decisions made prior to the observed changes in average marginal 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 response of the aggregate unemployment rate to tax cuts. Specifically, we can view the impulse response function (IRF) of the aggregate unemployment rate as a *weighted* sum of the IRFs of the age-specific unemployment rates,

where the weights are (sample averages of) the age-specific labor force shares:

$$\widehat{du}_h \approx \sum_{a \in \mathcal{A}} \bar{\phi}_a^{\text{LF}} \times \widehat{du}_{a,h}, \quad (7)$$

where \widehat{du}_h and $\widehat{du}_{a,h}$ indicate the IRFs of the aggregate unemployment rate and age-specific unemployment rates, respectively, and h is the number of years after the initial shock to the AMTR. Note that the impulse response of the counterfactual unemployment rate, $\widehat{du}_h^{\text{FLFS}}$, shown in panel B of Figure 7, guarantees that the right-hand side of (7) is indeed a strikingly good approximation of the impulse response of the actual unemployment rate, \widehat{du}_h , if we consider the entire sample period 1950-2006. With the IRF's approximation in (7) at hand, we can decompose the contribution of each age group to the aggregate response to tax cuts. Note that if there was no heterogeneity in the IRFs across age groups, then the labor force shares would become irrelevant as $\sum_{a \in \mathcal{A}} \bar{\phi}_a^{\text{LF}} = 1$ by construction. Therefore, 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.

We next establish that the response to tax cuts of the aggregate U.S. unemployment rate in Figure 4 in fact 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 U.S. labor force affect the response of the aggregate unemployment rate to tax cuts.

Figure 8 shows the dynamic responses of age-specific unemployment rates to an equally-sized 1 percentage point cut in the AMTRs. The estimates display stark differences in the responses of the young, prime-age, and old workers. In panels A and B, the unemployment rates for the 16-19 and 20-24 years old fall by 1 percentage point at the peak of the response, that occurs 3 years after the initial shock. The magnitude of these responses is somewhat larger than the 0.7 percentage points fall of the aggregate U.S. unemployment rate in response to a shock of the same size. For the 25-34 years old, instead, the unemployment rate falls by nearly 0.8 percentage points, which is then more in line with the response of the aggregate unemployment rate of 0.7 percentage points. However, the responses of unemployment rates for the age groups 35-44, 45-54, and 55 years and older, are nearly half as large as those of the 16-19 and 20-24 years old. We note that, despite the sizable differences in the magnitude of the responses, all age groups preserve a hump-shaped response to tax cuts which is consistent with the response of the aggregate unemployment rate in Figure 4.

In summary, the results in this section provide evidence of substantial heterogeneity in the responsiveness to tax shocks of unemployment by age. Such heterogeneity is the prerequisite for a quantitatively important role of age composition of the labor force in determining the aggregate unemployment response to tax cuts.

4.2 Age Composition and Aggregate Unemployment Response

We now turn to quantify the contribution of each age group to the response of the aggregate U.S. unemployment rate to tax shocks. Specifically, we decompose the impulse response of the unemployment rate of 16 years and older, shown in Figure 4, into additive *shares* that measure the relative contribution of each group to the aggregate unemployment response.

Shares of the aggregate unemployment response by age. Next, we use the IRF's approximation in (7) such that $\widehat{du}_h \approx \sum_{a=16}^{65+} \bar{\phi}_a^{\text{LF}} \times \widehat{du}_{a,h}$, where $\bar{\phi}_a^{\text{LF}}$ are the sample averages of the age-specific labor force shares, for 1950-2006, and $\widehat{du}_{a,h}$ are the estimated IRFs of actual age-specific unemployment rates, as shown in Figure 8. Hence, each age group accounts for \mathbf{share}_h^a of the response of the aggregate unemployment rate:

$$\mathbf{share}_h^a \equiv \bar{\phi}_a^{\text{LF}} \times \frac{\widehat{du}_{a,h}}{\widehat{du}_h}, \quad (8)$$

with $\sum_{a=16}^{65+} \mathbf{share}_h^a = 1$ at any horizon $h = 1, \dots, 5$ (years after the shock). As defined in (8), the share of each group in the aggregate unemployment response to a tax shock is calculated as the ratio of impulse responses (IRF-ratio), weighted by age-specific labor force shares. Table 2 shows the results of the age decomposition. Two extended age groups account for the bulk of the aggregate unemployment response to tax cuts. Specifically, the age groups 20-34 and 35-54 account for nearly 88 percent of the aggregate response in the first year after the shock, and for nearly 80 percent of the response from the second year after the shock onward. The age groups 16-19 and 55-64, combined, account for most of the remaining share of the response of the aggregate unemployment rate, whereas the age group of the 65 years and older is in fact negligible for nearly all years after the initial tax shock.

Note that the age-specific share of the aggregate unemployment response, as defined in (8), depends on both the average of the age-specific labor force share, $\bar{\phi}_a^{\text{LF}}$, and the ratio of the impulse responses of the age-specific to the aggregate unemployment rate, $\widehat{du}_{a,h}/\widehat{du}_h$. In principle, then, differences by age along both dimensions jointly determine the quantitative importance of the different age groups. How much of the age-specific heterogeneity in \mathbf{share}_h^a ,

shown in Table 2, is due to the differences in labor force shares by age as opposed to the ratio of impulse responses? To answer this question, we construct a counterfactual age-specific share, $\mathbf{share}_h^{a,FLFS}$, in which average labor force shares are fixed at the same value across age groups:

$$\mathbf{share}_h^{a,FLFS} \equiv \frac{1}{n_a} \times \frac{\widehat{du}_{a,h}}{\widehat{du}_h}, \quad (9)$$

where $n_a = 5$ is the number of age groups considered. Table 3 reports the results for the counterfactual decomposition in (9). Note that any age-specific heterogeneity in $\mathbf{share}_h^{a,FLFS}$ now comes exclusively from the heterogeneity in the unemployment rate responses to tax cuts across different age groups. Hence, the difference between the age-specific shares with and without fixed labor force shares can be entirely attributed to the age composition of the labor force. The results point in fact to a quantitatively important role of age composition. Specifically, the two extended age groups 20-34 and 35-54 now account for 76 percent of the aggregate unemployment response in the first year after the shock, and for approximately 63 percent from the second year after the shock onward. These figures are considerably smaller than those in Table 2. Age composition alone is responsible for a decrease of 12 percentage points for the first year after the shock, and 17 percentage points for the second year after the shock onward. Most of these differences are due to the changes in the relative shares of the 35-54 years old. This is because the 35-54 years old are relatively unresponsive to tax cuts as compared to the aggregate unemployment rate (see panel D and E, in Figure 8), but they represent on average 42 percent of the U.S. labor force, for the period 1950-2006. By contrast, the shares of the 16-19 years old raise by 7 percentage points for the first year after the shock and by approximately 11 percentage points from the second year after the shock onward. This is because the 16-19 years old are responsive to tax cuts (see panel A, in Figure 8), but they represent on average only 7 percent of the labor force. See Table 4 for average labor force shares by age group, for the period 1950-2006.

Unemployment elasticities by age. We now investigate the extent to which the age-specific heterogeneity in the unemployment rate responsiveness to tax shocks, as measured by the IRF-ratio in (8), can be attributed to differences in unemployment elasticities across age groups as opposed to differences in average unemployment rates. To this aim, we use a slightly modified version of the share in (8):

$$\mathbf{share}_h^a \equiv \bar{\phi}_a^{LF} \times \frac{\bar{u}_a}{\bar{u}} \times \frac{\hat{\epsilon}_{a,h}^u}{\hat{\epsilon}_h^u}, \quad (10)$$

where \bar{u}_a and \bar{u} are averages of age-specific and aggregate unemployment rates, respectively, and $\hat{\epsilon}_{a,h}^u \equiv \widehat{du}_{a,h}/\bar{u}_a$ and $\hat{\epsilon}_h^u \equiv \widehat{du}_h/\bar{u}$ are unemployment rate elasticities of age-specific and aggregate unemployment rates, respectively. As re-written in (10), the share of each group equals the ratio of the age-specific to the aggregate unemployment elasticity (elasticity-ratio), weighted by the product of the age-specific labor force share, and the ratio of the average age-specific to the aggregate unemployment rate (UNR-ratio).

Table 4 shows UNR-ratios by age group, for the period 1950-2006. Unemployment rates decrease monotonically with age. This age profile of unemployment rates is a stylized fact that theories of worker turnover and life-cycle unemployment have successfully explained (see Jovanovic, 1979; Chéron et al., 2013; Esteban-Pretel and Fujimoto, 2014; Papageorgiou, 2014; Gervais et al., 2014; Menzio et al., 2015). Note that these differences are quantitatively large. Specifically, the average unemployment rate of 16 years and older is 5.64 percent; the unemployment rate of the 16-19 years old is 15.63 percent, that is nearly 2.8 times higher than the average of the aggregate unemployment rate, whereas the unemployment rate of the 20-24 years old is 9 percent, that is 1.6 times higher than that of the 16 years and older. For the 25-34 years old, instead, the unemployment rate averages 5.29 percent, whereas the unemployment rates for the remaining age groups (35-44, 45-54, 55-64, and 65 years and older) are nearly 30 percent lower than the average of the aggregate unemployment rate.

Next, we establish new facts on the life-cycle profile of unemployment elasticities to tax shocks. We re-estimate the proxy SVAR using the unemployment rate in logs, separately for each each group, such that we recover unemployment elasticities by age. Table 5 reports the unemployment elasticities estimates by age group for the first year (“impact elasticity”) and the second year after the shock (“lagged elasticity”). The estimates provide evidence of an inverted U-shaped life-cycle profile of unemployment elasticities; the least elastic are the 16-19 years old and the 65 years and older, whereas the most elastic are the three age groups of 25-34, 35-44, and 45-54 years old. Same life-cycle patterns hold for unemployment elasticities up to five years after the shock (see Table B.1, in Appendix B). We emphasize that these findings differ from, and hence complement, the stylized fact that cyclical volatility in labor market conditions declines with age (see Clark and Summers, 1981; Gomme et al., 2005; Jaimovich and Siu, 2009; Jaimovich et al., 2013). These age-specific differences in unemployment elasticities are new life-cycle facts, that we argue can also be instrumental in disciplining theories of life-cycle unemployment, as they provide overidentifying restrictions for quantitative analysis of taxes and unemployment.

Table 2: Shares of Aggregate Unemployment Response by Age

h (years after shock):	1	2	3	4	5
\mathbf{share}_h^{16-19}	5.54	11.19	11.56	10.69	7.62
\mathbf{share}_h^{20-34}	51.96	46.53	44.46	43.33	42.96
\mathbf{share}_h^{35-54}	35.80	33.60	34.04	35.27	38.66
\mathbf{share}_h^{55-64}	6.16	7.42	8.53	9.42	10.20
\mathbf{share}_h^{65+}	0.54	1.26	1.41	1.29	0.56

Notes: See equation (8) for the definition of \mathbf{share}_h^a . Age-specific shares are reported in percent such that $\sum_{a=16}^{65+} \mathbf{share}_h^a = 100$ (column-wise summation).

Table 3: Counterfactual Shares of Aggregate Unemployment Response by Age

h (years after shock):	1	2	3	4	5
$\mathbf{share}_h^{16-19,FLFS}$	12.79	22.86	23.45	22.14	17.09
$\mathbf{share}_h^{20-34,FLFS}$	48.56	40.20	37.57	36.57	37.82
$\mathbf{share}_h^{35-54,FLFS}$	27.65	22.78	22.96	24.32	28.90
$\mathbf{share}_h^{55-64,FLFS}$	8.51	9.07	10.36	11.68	13.71
$\mathbf{share}_h^{65+,FLFS}$	2.49	5.09	5.66	5.29	2.48

Notes: See equation (9) for the definition of $\mathbf{share}_h^{a,FLFS}$. Age-specific shares with fixed labor force shares are reported in percent such that $\sum_{a=16}^{65+} \mathbf{share}_h^{a,FLFS} = 100$ (column-wise summation).

Table 4: Average Unemployment Rates and Labor Force Shares by Age

Age group:	16+	16-19	20-24	25-34	35-44	45-54	55-64	65+
Avg. UNR	5.64	15.63	9.01	5.29	4.04	3.64	3.62	3.51
Avg. UNR-ratio	1	2.77	1.60	0.94	0.72	0.65	0.64	0.62
Avg. LFS	100	7.03	11.57	23.96	22.96	19.18	11.75	3.55

Notes: Average unemployment rate (UNR) and labor force share (LFS), for 1950-2006, are reported in percent. The second row indicates average unemployment rates by age, relative to that of 16+ years old (UNR-ratio). See Appendix A for data sources.

Table 5: Unemployment Elasticities by Age

Age group:	16+	16-19	20-24	25-34	35-44	45-54	55-64	65+
Impact elas.	1.52	0.25	1.27	2.31	1.99	2.11	1.36	0.15
Impact elas.-ratio	1	0.16	0.84	1.52	1.31	1.39	0.89	0.10
Lagged elas.	2.92	1.05	3.11	3.47	3.56	3.67	3.23	1.58
Lagged elas.-ratio	1	0.36	1.07	1.19	1.22	1.26	1.11	0.54

Notes: “Impact elas.” refers to the unemployment rate elasticity of a specific age group at horizon $h = 1$ (one year after the shock); “Lagged elas.” refers to the unemployment rate elasticity of a specific age group at horizon $h = 2$ (two years 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 rate of a specific age group and a common set of regressors, as specified in (1), for 1950-2006. Elasticities are reported in percent. “Impact elas.-ratio” refers to the unemployment rate impact elasticity by age, relative that of 16+ years old. “Lagged elas.-ratio” refers to the unemployment rate lagged elasticity by age, relative that of 16+ years old. See Table B.1, in Appendix B, for elasticities estimates up to 5 years after the shock.

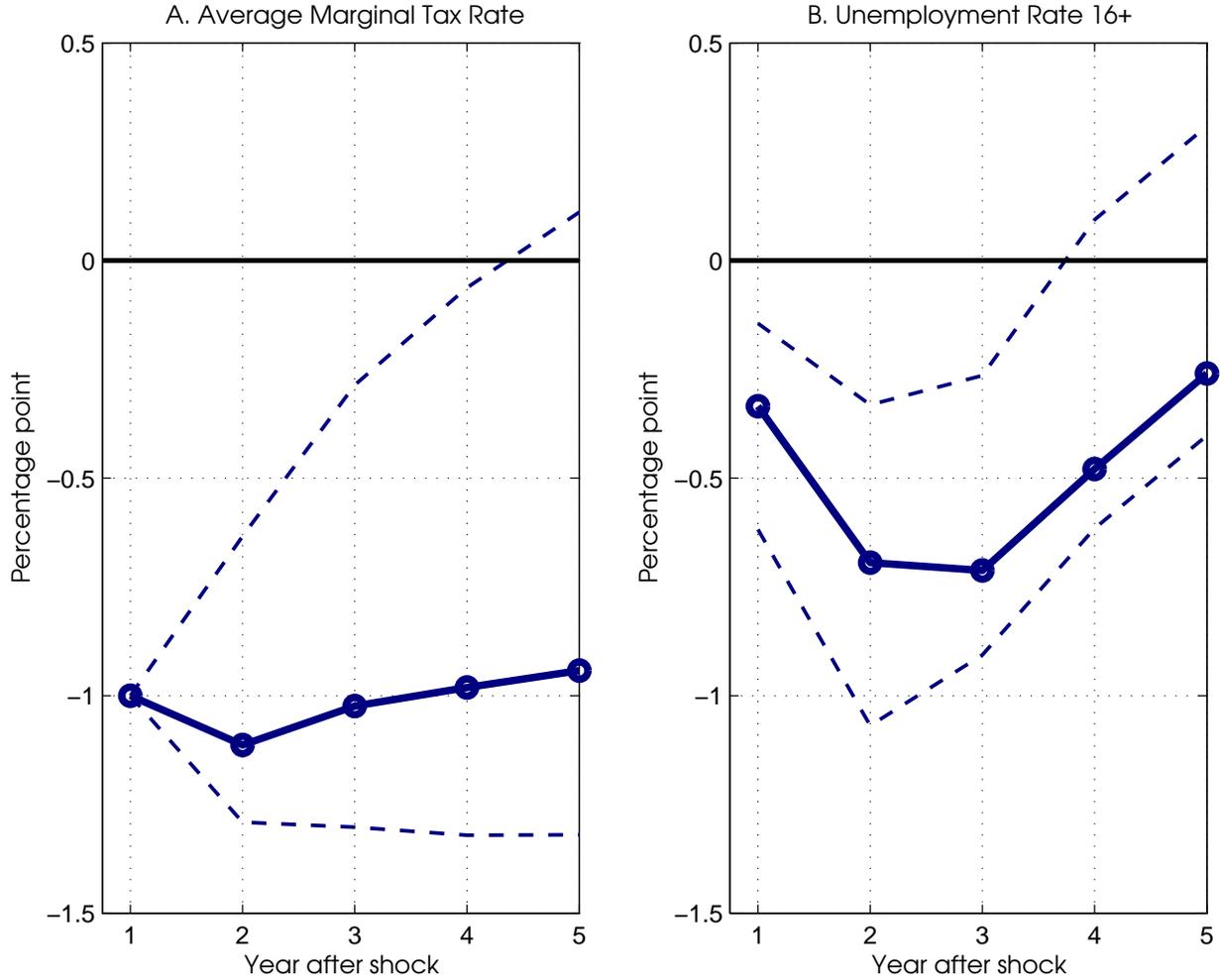


Figure 4: Unemployment Rate Response to a Tax Cut

Notes: The figure shows the response to a 1 percentage point cut in the average marginal personal income tax rate. Full lines with circles are point estimates; dashed lines are 95 percent confidence bands.

4.3 Aging of the Baby Boomers: Quantitative Implications

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 resembles that in [Shimer \(1999\)](#) and [Jaimovich and Siu \(2009\)](#), where the authors quantify the role of age composition of the U.S. workforce for low-frequency movements in the aggregate unemployment rate and cyclical volatility in hours worked, respectively. 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

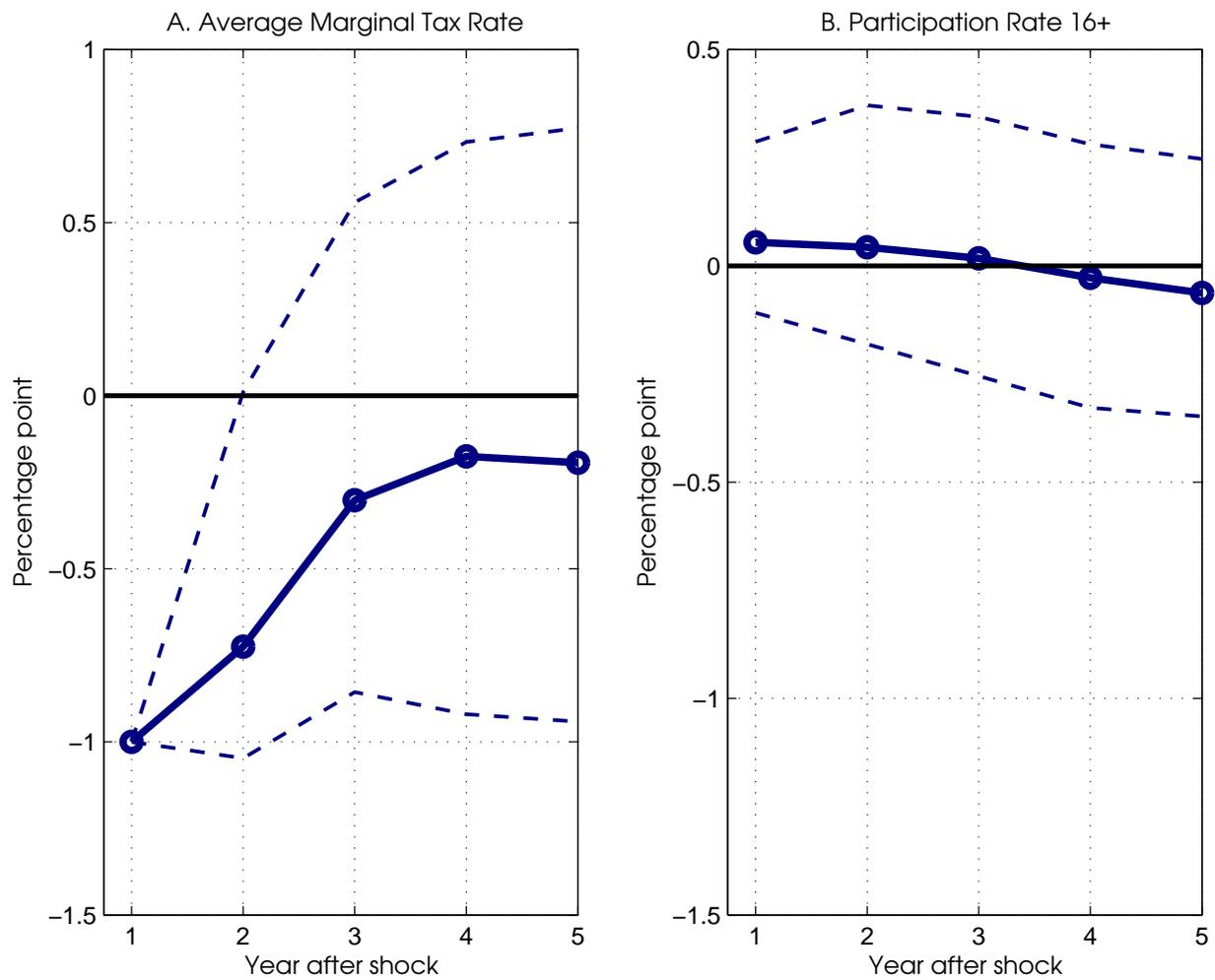


Figure 5: Participation Rate Response to a Tax Cut

Notes: The figure shows the response to a 1 percentage point cut in the average marginal personal income tax rate. Full lines with circles are point estimates; dashed lines are 95 percent confidence bands.

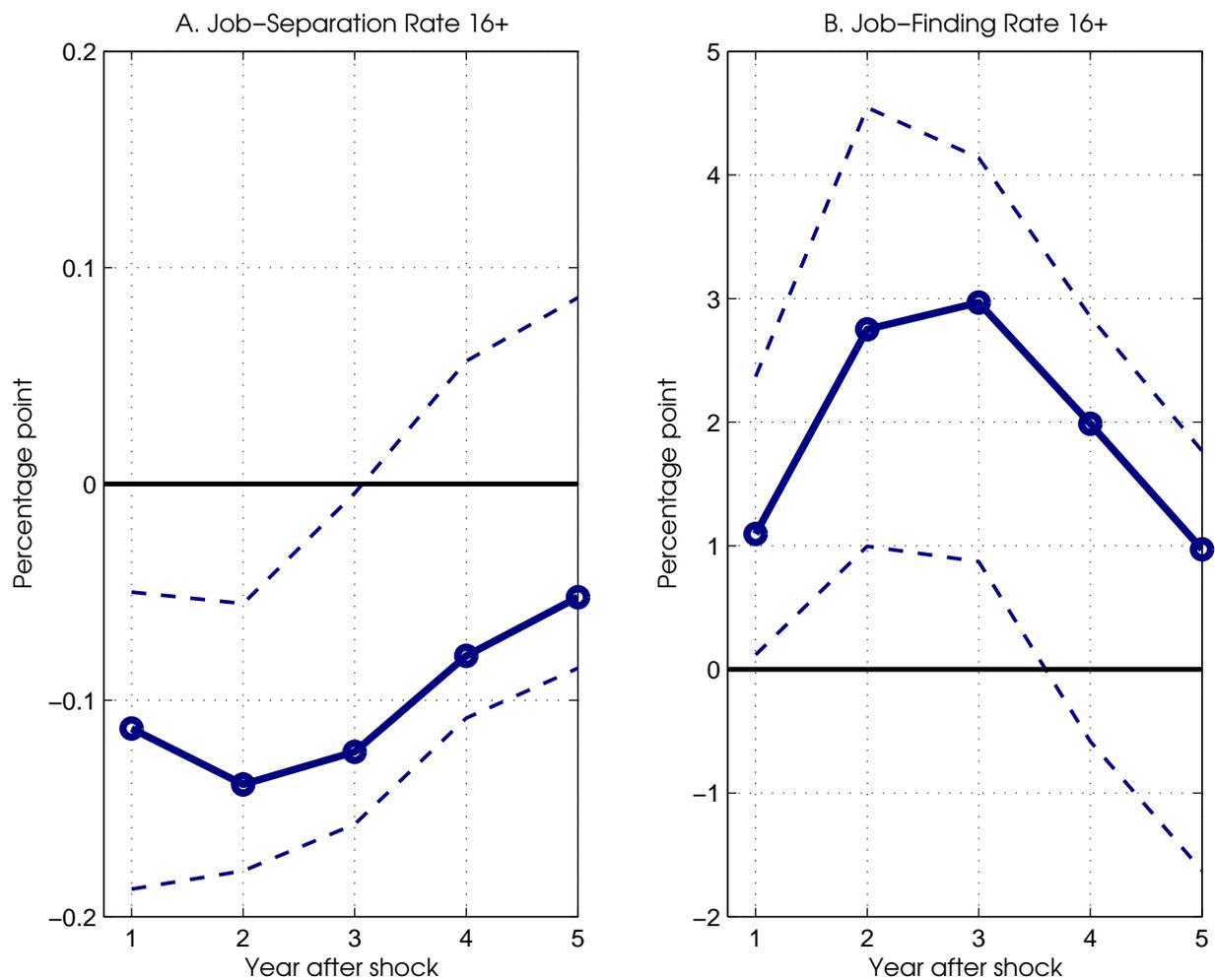


Figure 6: Job-Separation and Job-Finding Rate Response to a Tax Cut

Notes: The figure shows the response to a 1 percentage point cut in the average marginal personal income tax rate. Full lines with circles are point estimates; dashed lines are 95 percent confidence bands. Data for job-separation and job-finding rates was constructed by Robert Shimer (see [Shimer, 2012](#), for details).

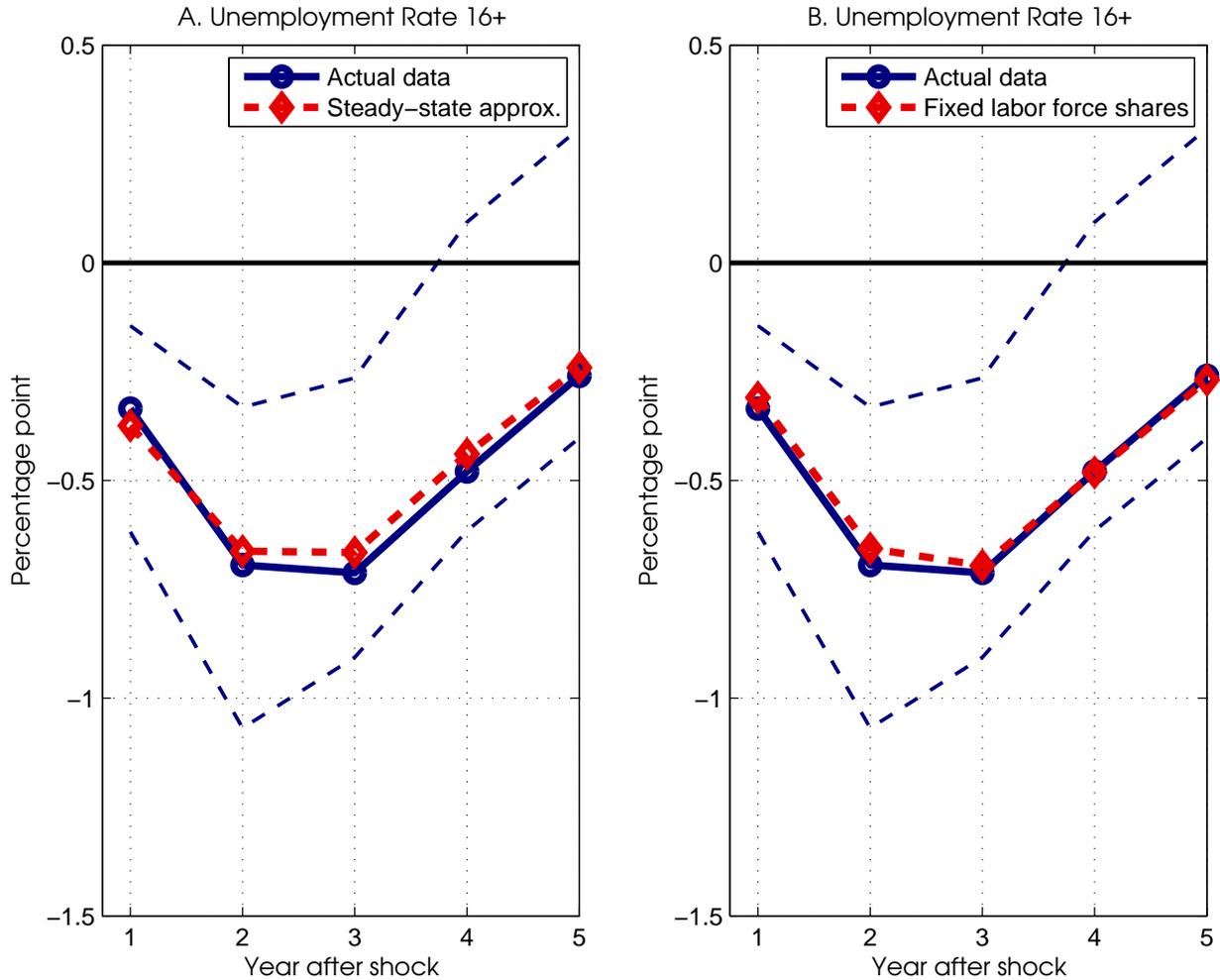


Figure 7: Unemployment Rate Response to a Tax Cut—Goodness of Fit of Steady-State and Fixed Labor Force Shares Approximation

Notes: In panel A and B, full lines with circles are point estimates for the response to a 1 percentage point cut in the average marginal personal income tax rate; dashed lines are 95 percent confidence bands. In panel A, dashed line with diamonds shows the steady-state approximation of the response for the actual unemployment rate, as implied by equation (4). In panel B, dashed line with diamonds shows the response of the counterfactual unemployment rate with fixed age-specific labor force shares.

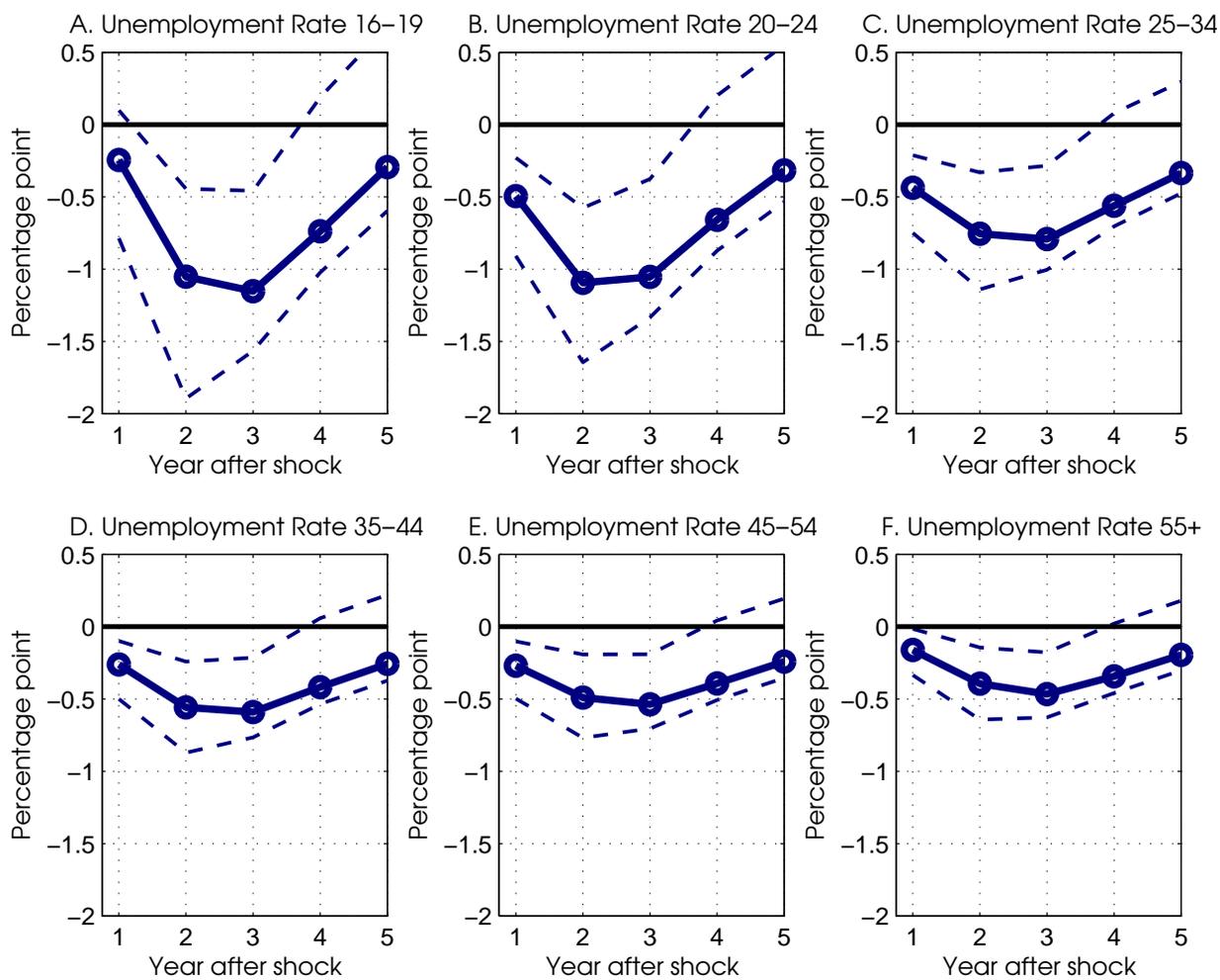


Figure 8: Unemployment Rate Response to a Tax Cut by Age

Notes: The figure shows the response to a 1 percentage point cut in the average marginal personal income tax rate. Full lines with circles are point estimates; dashed lines are 95 percent confidence bands.

in the late-1970s and their subsequent 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 workers, 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. Next, we show that the demographic change experienced by the U.S. labor market also has quantitatively important implications for the effectiveness of countercyclical fiscal policy. We find that the aging of the baby boomers considerably reduces the effects of tax cuts on aggregate unemployment.

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 unemployment elasticities estimated instead over the entire sample period 1950-2006, as shown in [Table 5](#). 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 U.S. unemployment rate to tax cuts.

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

$$\widehat{du}_{h,t}^{\text{AC-adj}} \equiv \sum_{a=16}^{65+} \bar{\phi}_{a,t}^{\text{LF}} \times \bar{u}_{a,t} \times \hat{\epsilon}_{a,h}^u, \quad (11)$$

where the time subscripts indicate that the AC-adj aggregate unemployment response, $\widehat{du}_{h,t}^{\text{AC}}$, is allowed to vary over time based on the observed demographic trends, that drive changes in age-specific labor force shares. We use [equation \(11\)](#) to generate the adjusted unemployment responses to an equally-sized tax cut, at 5-year intervals, from 1950 to 2005. Is this exercise informative of the propagation mechanism of tax shocks? Note that this exercise assumes that age-specific unemployment elasticities are independent of age composition. Specifically, it assumes the absence of indirect effects of changing age composition of the labor force on the aggregate unemployment response via changes in age-specific unemployment elasticities. The responses in [\(11\)](#) tell then 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, to the extent that the age composition of the U.S. labor force has dramatically changed over the post-war period, one would expect the aggregate unemployment response to tax cuts to

differ based on the observed changes in the average age of the labor force. Next, we show that this is indeed the case. Figure 9 shows the counterfactual responses of the aggregate U.S. unemployment rate, as constructed in (11), for the first year (“impact response”) and the second year after the shock (“lagged response”). The results indicate large changes in the response of the aggregate unemployment rate to tax cuts. The peak impact and lagged responses occur in the mid-1970s; the peak impact response to a 1 percentage point cut in AMTRs is 0.42 percentage points, that is nearly 50 percent larger than the response of 0.27 percentage points in 2005, whereas the peak lagged response is 0.81 percentage points, that is nearly 56 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. Figure 10 shows that these changes are indeed associated with the shifts in the age composition of the labor force. Specifically, the responses closely track the share of the 35-54 years old in the labor force. The entry of the baby boomers in the labor force in the 1970s caused a fall in the share of the 35-54 years old of nearly 10 percentage points. At the same time, the share of the 20-34 years old increased by nearly the same amount. Since the young are more responsive to tax cuts than prime-age workers, the responsiveness of the aggregate unemployment rate dramatically increased over the period. However, as the aging of the baby boomers unfolds, the effects of tax cuts on aggregate unemployment are reduced to a level comparable to that of early-1950s.

5 Conclusion

In this paper, we investigate the consequences of demographic change for the propagation of tax shocks in the United States over the post-WWII period. After isolating exogenous variation in average marginal tax rates in SVARs 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 prime-age and old workers in the labor force. 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 cuts. We find that the aging of the baby boomers considerably reduces the effects of tax cuts on aggregate unemployment. These results indicate that the age composition of the labor force is a potentially important transmission channel of tax cuts, that deserves then further attention in fiscal policy analysis. In our view, there are

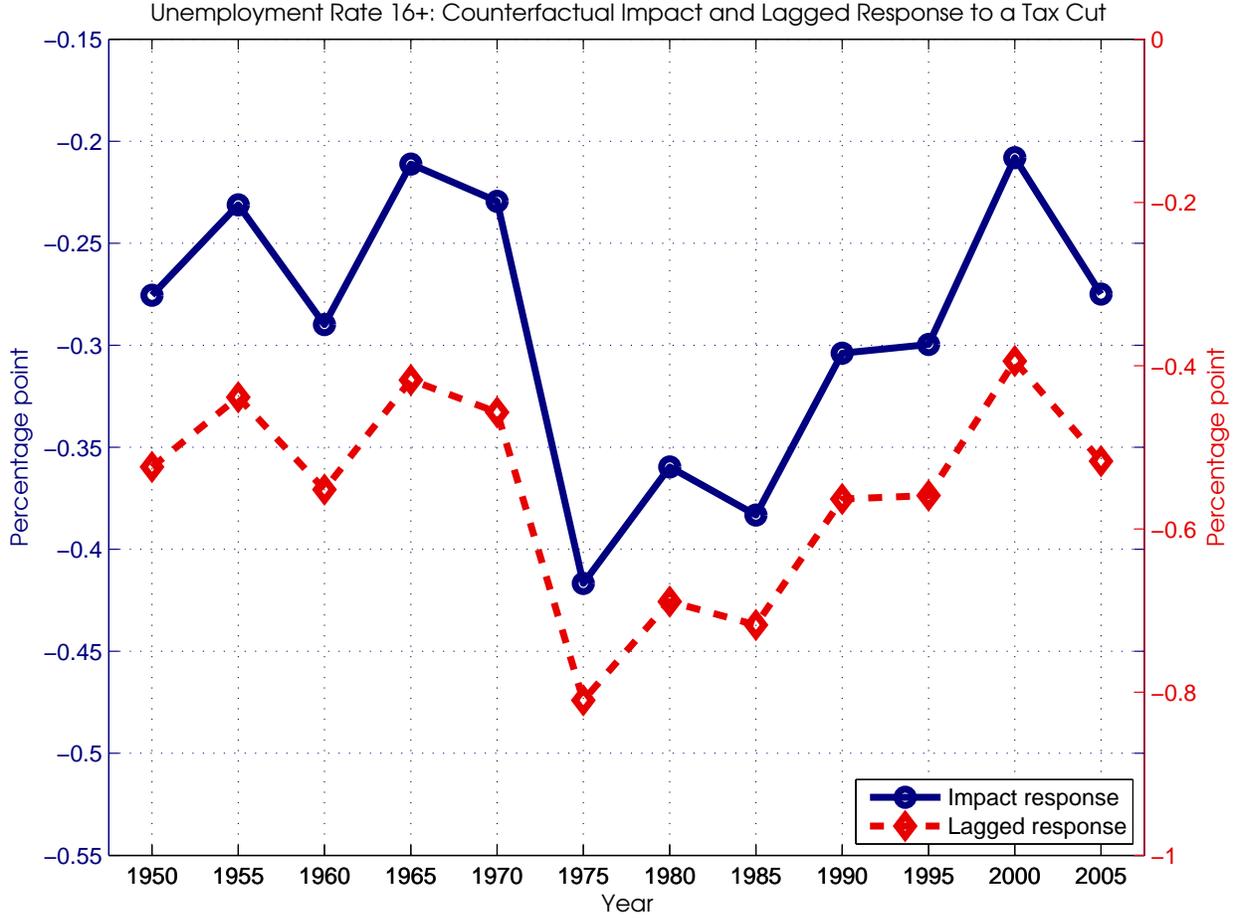


Figure 9: Unemployment Rate Response to a Tax Cut—Accounting for Trends in the Age Composition of the Labor Force

Notes: The figure shows the counterfactual responses of the unemployment rate of 16 years and older to a 1 percentage point cut in the average marginal personal income tax rate. “Impact response,” full line with circles (left axis), shows the counterfactual response of the unemployment rate at horizon $h = 1$ (one year after the shock); “Lagged response,” dashed line with diamonds (right axis), shows the counterfactual response of the unemployment rate at horizon $h = 2$ (two years after the shock). Counterfactual impact and lagged responses are constructed using equation (11).

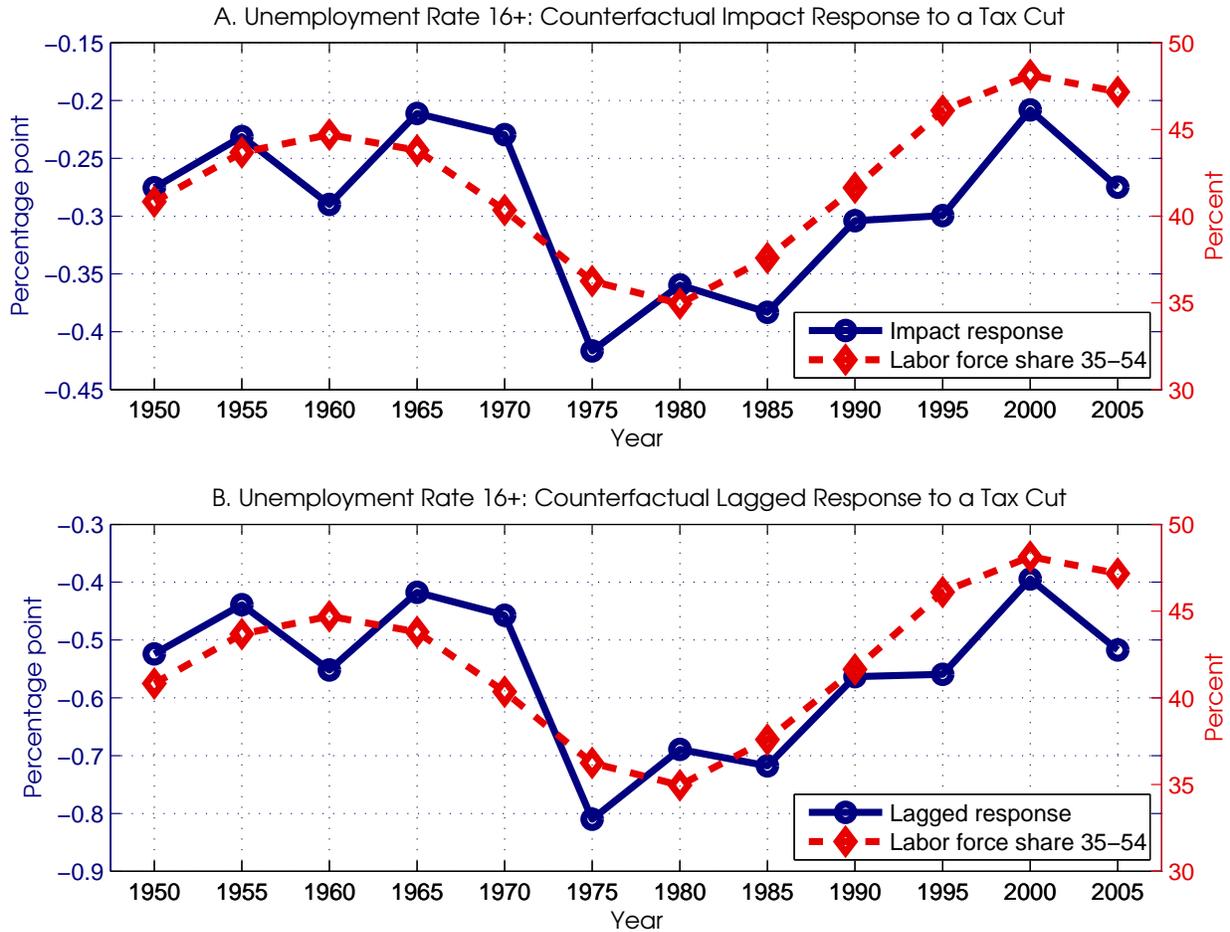


Figure 10: Demographics and Unemployment Rate Response to a Tax Cut

Notes: In panel A, full line with circles (left axis) shows the counterfactual response of the unemployment rate at horizon $h = 1$ (one year after the shock, “impact response”). In panel B, full line with circles (left axis) shows the counterfactual response of the unemployment rate at horizon $h = 2$ (two years after the shock, “lagged response”). Counterfactual impact and lagged responses to a 1 percentage point cut in the average marginal personal income tax rate are constructed using equation (11). In panels A and B, dashed lines with diamonds (right axis) show the labor force share of the 35-54 age group. Labor force is defined as employed plus unemployed workers of 16 years and older, in accord with the definition of the Bureau of Labor Statistics (BLS).

high returns to a theoretical understanding of why unemployed workers respond differently to tax cuts over the life cycle, and what are the implications of demographic change for the transmission mechanism of tax policy. In [Ferraro and Fiori \(2016\)](#), we address these issues through the lens of a quantitative theory.

Appendix

A Data Sources

Monthly data for the U.S. labor force, unemployment rates, labor force participation rates, employment and unemployment levels, and population for the overall U.S. economy and by age groups are produced by the Bureau of Labor Statistics (BLS) and publicly available at the Current Population Survey (CPS) home page at <http://www.bls.gov/cps/>. Monthly job-separation and job-finding rates are constructed based on Shimer (2012) and publicly available at Robert Shimer's website at <https://sites.google.com/site/robertshimer/research/flows>. Data on average marginal income tax rates has been tabulated by Robert Barro and Charles Redlick in Barro and Redlick (2011). Data for personal income tax base, government purchases, and federal debt (all in real per capita terms) are from Mertens and Ravn (2013) dataset and publicly available at Karel Mertens's website at <https://mertens.economics.cornell.edu/research.htm>. Personal income tax base is defined as personal income (NIPA Table 2.1, line 1) less government transfers (NIPA Table 2.1, line 17) plus contributions for government social insurance (NIPA Table 3.2, line 11).

B Additional Tables and Figures

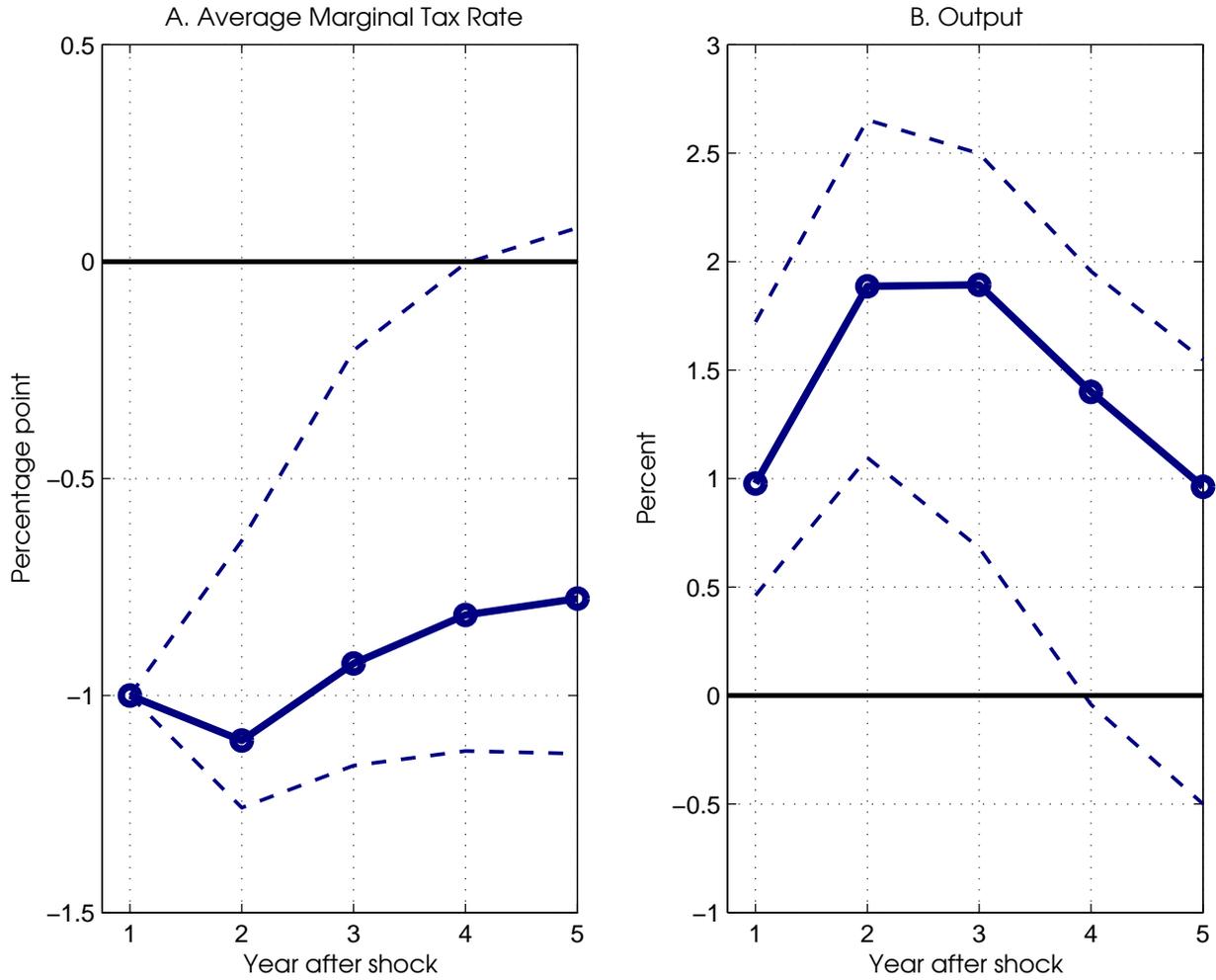


Figure B.1: Output Response to a Tax Cut

Notes: The figure shows the response to a 1 percentage point cut in the average marginal personal income tax rate. Full lines with circles are point estimates; dashed lines are 95 percent confidence bands.

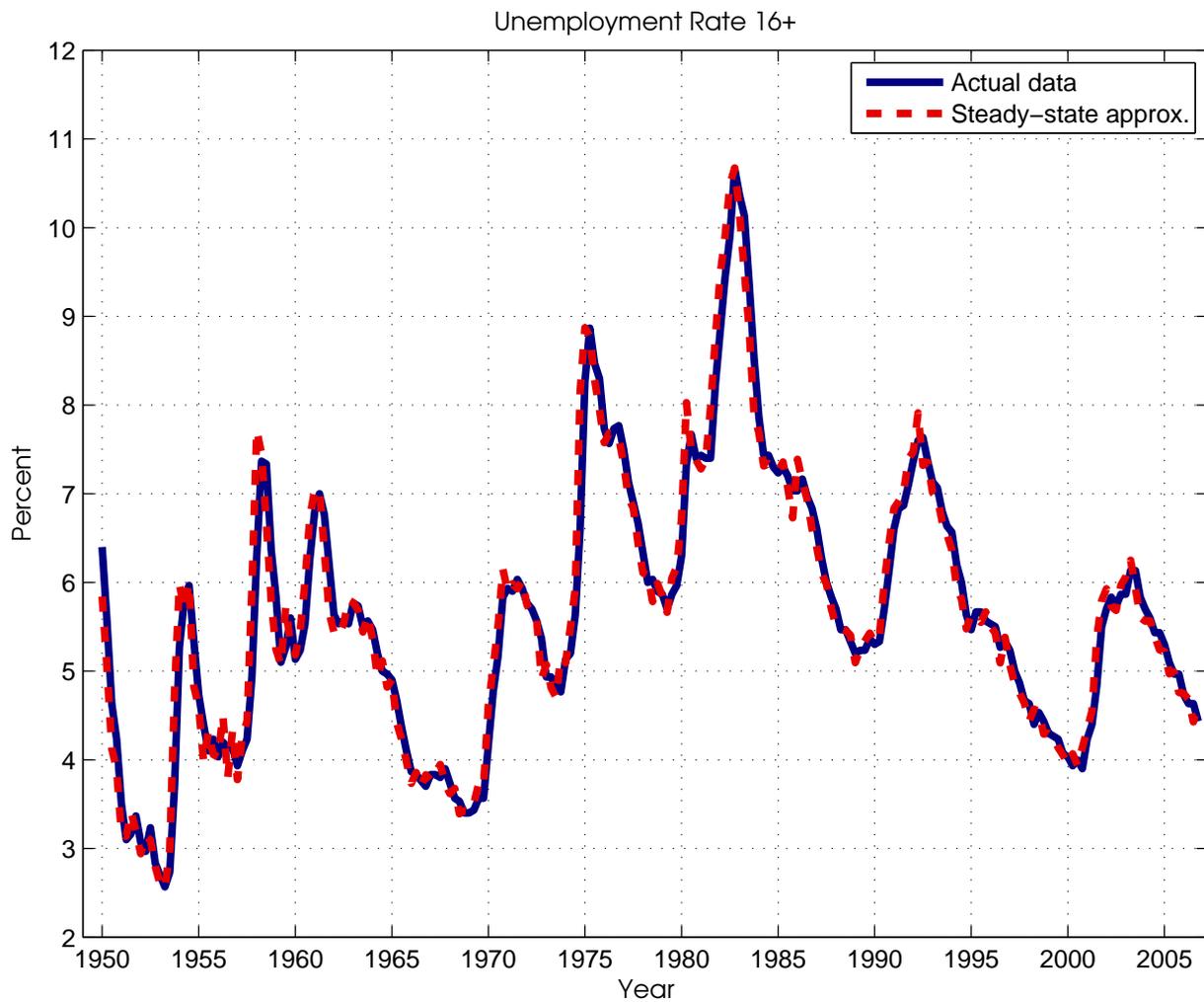


Figure B.2: Unemployment Rate—Goodness of Fit of Steady-State Approximation

Notes: The figure shows the unemployment rate of 16 years and older (full line) and the counterfactual unemployment rate under the steady-state approximation (dashed line). The steady-state approximation of the actual unemployment rate is constructed as $u_t^{ss} = s_t / (s_t + f_t)$. Data for job-separation, s_t , and job-finding rates, f_t , was constructed by Robert Shimer (see [Shimer, 2012](#), for details).

Table B.1: Unemployment Elasticities by Age (up to 5 years after the shock)

Age group:	16+	16+ ^{FLFS}	16-19	20-24	25-34	35-44	45-54	55-64	65+
Elas. at year 1	1.52	1.50	0.25	1.27	2.31	1.99	2.11	1.36	0.15
Elas. at year 2	2.92	2.93	1.05	3.11	3.47	3.56	3.67	3.23	1.58
Elas. at year 3	3.38	3.44	1.15	3.30	4.22	4.13	4.26	4.05	2.05
Elas. at year 4	2.53	2.62	0.74	2.32	3.26	3.22	3.36	3.29	1.44
Elas. at year 5	1.51	1.62	0.29	1.28	2.10	2.16	2.26	2.17	0.53

Notes: “Elas.” refers to the unemployment rate elasticity of a specific age group at horizon $h = 1, \dots, 5$ (years after the shock). Each of the elasticities estimates are based on a separate SVAR system that includes the log of the unemployment rate of a specific age group and a common set of regressors, as specified in (1), for 1950-2006. Elasticities are reported in percent. The column labeled “16+^{FLFS}” refers to the counterfactual unemployment rate of 16 years and older with fixed labor force shares as in (6).

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