The Marginal Net Taxation of Americans' Labor Supply

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Abstract

The U.S. has a plethora of federal and state tax and benefit programs, each with its own, typically major, work incentives and disincentives. Collectively, they place a large share of workers, particularly low-wage workers, in high net (of benefits) tax brackets. This paper uses the Fiscal Analyzer (TFA) to assess how our fiscal policies, in unison, impact work incentives. TFA is a life-cycle, consumption-smoothing program that incorporates cash-flow constraints and all major federal and state tax and benefit policies. We use TFA in conjunction with the 2019 Survey of Consumer Finances to calculate Americans' remaining lifetime marginal net tax rates (LMTRs), defined as the present expected (over household survival paths) value of additional current and future taxes, net of benefits, divided by a given increase in current labor earnings. Thus, the LMTR captures double taxation – the increase in future taxes, including asset income and sales taxes, or reduction in future benefits, including those due to income- and asset-based tests – associated with saving a portion of one's additional current earnings. We calculate annual future net taxes assuming all households smooth their living standards per equivalent adult, subject to borrowing constraints, and supply labor exogenously. These behavioral assumptions let us study labor supply distortions independent of responses to such distortions. Our findings are striking. Over half of working-age Americans face LMTRs above 40 percent. One fourth of households in the bottom remaining lifetime-resource (human plus non-human wealth) quintile face LMTRs above 50 percent; one tenth face LMTRs above 70 percent. Such extremely high work disincentives may be locking large segments of the poor into poverty. These disincentive would be roughly one quarter larger were benefit take-up complete. Top resource households also face major work disincentives. The median LMTR for those in the top 1 percent of the resource distribution is 57.9 percent. We find remarkable dispersion in both LMTRs and current-year marginal net tax rates (CMTRs) even controlling for age, state, and resource level. For example, 5.1 percent of bottom-quintile households face LMTRs above 100 percent; 4.5 percent face negative rates. Simply eliminating bottom-quintile dispersion produces, under simplifying assumptions, efficiency gains as high as one quarter of that quintile's labor income. Finally, double taxation matters. The median LMTR is 43.1 percent – nearly one third larger than the 33.3 percent median CMTR, which ignores future net taxes generated by additional current earnings.

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1 Introduction

This paper aims to provide the most comprehensive and systematic measurement to date of U.S. work incentives and disincentives. A host of federal and state tax and benefit programs jointly determine Americans' marginal net tax brackets. Adopted with little apparent concern for their collective impact, most policies are highly non-linear, rendering lifetime budget constraints non-differentiable, discontinuous, and nonconvex. The sources of budget-frontier "kinks" (changes in slope), "notches" (discontinuities), and nonconvexities (where increases in income can lead to reduced marginal net tax rates and possibly multiple local optima), are complex provisions that condition tax payments and benefit receipts on labor income, asset income, total income, net assets, and household demographics. Earning more today can, if it elicits more saving, raise (lower) not just current, but also the entire panoply of future taxes (benefits). Such *double taxation* has been long discussed, but never carefully measured – one of our study's central tasks.

This paper focuses on marginal net tax rates and the incentives they present for individual behavior. Auerbach et al. (2023) uses a similar method to measure average lifetime net tax rates, i.e., to determine the progressivity of the fiscal system. As they show, average lifetime net tax rates rise sharply with lifetime resources. In simple tax/benefit systems with smoothly rising marginal net tax rates, average and marginal tax rates are closely related. But for U.S. households, the net tax system is anything but smooth, particularly for low wage workers who face severe income-related, benefit-program eligibility conditions. Hence, workers, particularly those with low wages, can de minimis or even negative average lifetime net tax rates, but very high lifetime marginal net tax rates.

The U.S. fiscal system comprises over 500 distinct tax and benefit programs with an array of work incentives and disincentives, some in the same program. The federal personal income tax's seven tax brackets, ranging in 2024 from 10 to 37 percent, are well known. But other programs can materially alter the net taxes workers face on extra earnings. Take the Earned Income Tax Credit (EITC). For singles with three children, it provides a 45 percent subsidy on the parent's first $17,400 of earnings. There is no credit for earning between $17,400 and $22,000. But earnings above $22,000 reduce the credit by 21 cent on the dollar. Social Security's 12.4 percent FICA tax hits workers on each dollar earned through $168,600.[1] California's state income tax has nine tax brackets – from 1 percent to 12.3 percent. Its state-level sales tax equals 7.25 percent, which translates into an effective 6.75 percent tax on labor earnings.

In Rhode Island, $766 in monthly Food Stamp benefits are available for households with three children with gross monthly income below $3,833. In Mississippi, the benefit is the same, but the threshold is lower – $2,694. A New Yorker can receive Medicaid as long as earnings are below $43,056. In Montana, the limit is $26,500. If you receive Social Security benefits before you reach January 1st of the year you'll attain the System's full retirement age, every dollar of earnings above $22,230 entails a 50 cent on-the-dollar loss in benefits due to the Earnings Test.[2] Receiving Social Security? If a special measure of modified adjusted gross income (MAGI) exceeds $25,000 ($32,000 if married filing jointly), every extra dollar earned can come at the cost of 50 cents in benefits and 85 cents if your MAGI measure exceeds $34,000 or $44,000 if married filing jointly.

Similarly complex provisions affect other important transfer programs. Earn $1 too much starting before participating in Medicare Part B, and your joint annual premium can rise by $2,515. Earn or save $1 too much and, depending on the state, lose thousands of dollars in your

[1] We assume that "employer-paid" FICA taxes are borne by workers in the form of lower pay net of these taxes. Also, we incorporate the offsetting marginal present value of additional benefits arising from additional covered earnings.

[2] The Adjustment of the Reduction Factor largely undoes the Earnings Test for most beneficiaries, but Social Security fails to advertise this fact.

own or your family members' Medicaid benefits. Hold $1 too much in assets and forfeit $2,000 in Supplemental Security Income (SSI). Earn an extra dollar in a Medicaid non-expansion state and qualify for thousands of dollars in Affordable Care Act (ACA) subsidies.

Our largest fiscal program – the federal personal income tax – generates a plethora of kinks in household intertemporal choice sets. The tax's seven brackets and standard deduction are the best known sources of kinks, but other provisions make the budget frontier non-differentiable as well. These include the Alternative Minimum Tax, the taxation of Social Security benefits, high-income Medicare wage- and asset-income taxes, the EITC, the Child Tax Credit (CTC), and the Child and Dependent Care Tax Credit (CDCTC). As for the 51 (including D.C.) states, 42 tax income and 46 tax sales. Moreover, as suggested, each state has its own version of federal benefit programs largely due to the dependence of eligibility cutoffs and benefit amounts on local economic conditions. Thus, there are 51 state-specific Medicaid, SNAP, Section-8 housing, ACA, TANF, and other benefit programs.[3] In addition, state income taxes have features parallel to those in the federal income tax. For example, 31 states have their own EITC and 14 states have their own CTC.

These and many other tax/transfer programs invite this paper's central questions: What are the typical *combined* remaining lifetime marginal net tax (gross tax less gross benefit) rates (LMTRs) facing American workers? How do median LMTRs differ by age and resource (human plus non-human wealth) level? What is the dispersion in LMTRs holding age and resource-level fixed? Is the fiscal system locking large shares of the poor into poverty by confronting them with very high net marginal tax rates? How important is double taxation as measured by the difference in lifetime- and current-year marginal net tax rates (CMTRs)?[4] How does state residency impact the incentive to work? How much higher would our LMTR and CMTR measures be were all workers to participate in all programs for which they are eligible? Finally, how large is the excess burden arising from the dispersion in marginal net taxation?

We address these issues by running respondents to the 2019 Survey of Consumer Finances (SCF) through The Fiscal Analyzer (TFA), a life-cycle consumption-smoothing software tool. TFA does its consumption smoothing subject to borrowing constraints and incorporates, in full detail, all major U.S. federal and state tax and transfer programs.[5] To better capture marginal tax-rate dispersion, we augment the SCF data with imputations of respondent-specific earnings growth, retirement age, welfare program take-up rates, and survival-path probabilities. Our imputations are based on data from the 2019 American Community Survey (ACS), the Health and Retirement Study (HRS), the Current Population Survey, and the 2019 Annual Social and Economic Supplement (ASEC) to the CPS. We also incorporate program-specific lags in adjusting federal and state taxes, welfare payments, and Social Security benefits for inflation.

Our study is intentionally limited in one critical dimension. We seek to understand Americans' work disincentives, not their responses to those disincentives. While past studies have considered behavioral responses[6], we leave such analysis for future research. Hence, we treat labor supply as exogenous. Were we to posit a structural model and study not just the impact

[3] Actually, ACA's premium subsidy is county specific. It depends on the second lowest-cost Silver plan in a qualifying household's county of residence. And the sales taxes in some states also vary by county or even by city.

[4] For households that aren't borrowing constrained, additional earnings lead to additional saving, higher future assets and asset income, potentially higher federal and state income taxes, higher future sales taxation, and, potentially, lower income- and asset-tested future benefits.

[5] TFA relies on MaxiFi Planner's computation engine. MaxiFi Planner is a personal financial planning tool developed by Laurence Kotlikoff's software company – Economic Security Planning, Inc. Although the computation engines are the same, MaxiFi Planner considers a much smaller set of benefit policies than does TFA.

[6] See Moffitt et al. (2012) for an excellent review of this literature.

of the fiscal system on intertemporal budgets, but reactions to the system, we'd necessarily need to decompose provisions and reactions to understand which was at play. Hence, this paper is a required first step toward a full evaluation of the impact of the U.S. fiscal system on labor supply.[7] This said, we do present an illustrative excess burden calculation, which focuses on the deadweight loss arising from taxing otherwise identical low-wage workers at different rates.

Our main experiment is calculating the LMTRs 2019 SCF household heads face in earning an extra $1,000 in 2019. Our findings are striking. Over half of working-age Americans face LMTRs above 40 percent. One in four low-wage workers face LMTRs above 50 percent, and one in ten face rates above 70 percent. Labor supply disincentives of low-wage workers would be greater still were there full benefit-program participation. The top 1 percent resource (net wealth plus human wealth) percentile also face extremely high LMTRs. Their median rate is 57.9 percent. Both LMTRs and CMTRs are remarkably dispersed, particularly among the poor. For example, among the poorest quintile in the 30-39 year-old age group, the 25th, 50th, and 75th LMTR percentile values are 27.2 percent, 41.5 percent, and 51.9 percent, respectively.

Double taxation matters. The overall median LMTR of 43.1 percent is nearly one third higher than the median CMTR of 33.3 percent. Depending on one's age and resources, LMTRs can far exceed CMTRs. Take the top 1 percent of 40-49 year-olds, their median LMTR and CMTR are 62.0 percent and 42.6 percent, respectively. State residence can also dramatically affect marginal net tax rates. Across all cohorts, the typical bottom-quintile household can lower its remaining lifetime marginal net tax rate by an extraordinary 97.5 percentage points by switching states. This remarkable result reflects the combination of low-income households' participation in welfare programs and the diversity of such programs across states.

Unlike Diamond (1998) and Saez (2001)'s theoretical optimal income tax predictions, we do not find a U-shaped pattern in which either LMTRs or CMTRs are higher for the poor and rich than for the middle class. Instead, both measures of work disincentives rise with resources. The median LMTR of the those in the bottom resource quintile is 37.5 percent. It's 41.0 percent in the middle quintile, 49.1 percent in the top quintile, and 57.9 percent for the top 1 percent. But benefit-program take up matters for this result. With full participation, LMTRs and CMTRs would both have U-shaped patterns. Assuming full participation, the median LMTR in the bottom resource quintile is 48.8 percent. It's 43.0 percent for the middle quintile and 49.2 for the top quntile. The corresponding full-participation CMTRs are 40.3, 34.8, and 36.4 percent. Non-participation reflects inertia, stigma, and reluctance to deal with multiple, complex benefit programs (see Moffitt 1983; Riphahn 2001; Yaniv 1997).

For many working-age Americans, the labor-supply options may simply comprise not working, working part time, and working full time. Accordingly, we calculate, for non-working, able-bodied SCF respondents of working age, the lifetime net tax rate on working full time or part time.[8] This rate is formed by dividing the present value increase in remaining lifetime net taxes by the present value increase in remaining lifetime earnings. For those in the lowest income quintile, the median full-time and part-time work taxes equals 45.0 percent and 40.6 percent, respectively. For top quintile households, these medians are even higher – 54.8 percent and 54.2 percent, respectively. Median current-year full-time and part-time work taxes are roughly 10 percentage

[7] Formulating a structural model requires global optimization given the non-differentiable, discontinuous, and non-convex nature of intertemporal budgets. Brumm et al. (2024) provides a new method of global optimization that, while still at an early stage, may permit analysis of behavioral responses to the entire U.S. fiscal structure. Certainly its stylized fiscal system, comprising the federal income tax brackets, a basic benefit for those earning less than $15,000, and the FICA tax, suffice to produce massive labor-supply distortions with some workers cutting their labor supplies in half to avoid losing basic benefits and excess burdens reaching as high as one quarter of lifetime spending.

[8] Non-working references out of the labor force, i.e., neither employed or unemployed. Able-bodied means not reporting receipt of disability benefits.

points lower across the entire resource distribution.

The next section provides three case studies detailing our LMTR and CMTR calculations. Section 3 briefly reviews prior studies measuring fiscal work incentives and disincentives. Section 4 presents our remaining lifetime framework. This and other sections, which describe our methodology and imputations, borrow heavily and, in some cases, verbatim, from Altig et al. (2024), Auerbach et al. (2023), and Altig et al. (2022). Section 5 describes TFA, including its iterative dynamic programming algorithm and the six ways one can confirm that its calculations are precise to the dollar. Section 6 briefly describes our aforementioned imputations, relegating details to the Appendix. Section 7 presents our findings. Section 8 estimates the cost of labor force entry of non-working households. Section 9 considers differences across states in marginal net taxation. Section 10 examines the impact of the size of income increases on lifetime and current-year marginal net tax rates. Section 11 presents a simple excess burden calculation. Section 12 concludes.

2 Understanding Extreme Marginal Net Tax Rates - Three Case Studies

To help clarify our diverse findings, we illustrate our LMTR and CMTR calculations for three SCF households facing markedly different marginal net tax rates. Case I describes a high-income, single earner with a much higher LMTR than CMTR. Case II is a low-income household with an LMTR well above 100 percent. Case III illustrates the potential for a household to have a negative LMTR while its CMTR is positive.

2.1 Case I

This household comprises a 44 year-old, college educated, single male who lives in Arizona. The respondent is a very high earner, placing him in the top resource quintile. As shown in table 1, he pays \$138,670 in current-year federal income taxes on a pre-tax income of \$438,541. The respondent's CMTR is 36.0 percent, but his LMTR is much higher – 58.2 percent.

Table 1: Breakdown of LMTR and CMTR sources, Case I in Arizona

	C Baseline	C Marginal	C Diff	L Baseline	L Marginal	L Diff
Federal Income Tax	138,670	138,978	308	1,938,780	1,939,229	449
State Income Tax	17,596	17,633	37	243,442	243,496	54
Other Taxes	27,991	28,006	15	526,437	526,516	79
Total Taxes	184,257	184,617	360	2,708,659	2,709,241	582
SNAP	0	0	0	0	0	0
TANF	0	0	0	0	0	0
Section 8	0	0	0	0	0	0
CCDF	0	0	0	0	0	0
Social Security	0	0	0	137,382	137,382	0
SSI	0	0	0	0	0	0
Medicare	0	0	0	48,927	48,927	0
Medicaid	0	0	0	0	0	0
ACA	0	0	0	0	0	0
Other Transfers	-0	-0	-0	-0	-0	-0
Total Transfer Payments	-0	-0	-0	186,309	186,309	-0
Net Taxes	**184,257**	**184,617**	**360**	**2,522,350**	**2,522,932**	**582**

Note: All numbers are calculated based on a \$1,000 increase in current-year earnings. Weighted Mean values are presented.

Double taxation under the federal income tax amounts, in this case, to \$141. This is a 14.1

percentage point contribution to this respondent's 58.2 percentage point LMTR. Double taxation via state income taxation contributes $17 in expected present value, and other taxes, primarily the state sales tax (Arizona's rate is 7.9 percent), add an additional $64.[9]

2.2 Case II

This case involves a bottom-resource quintile Idaho couple. Both spouses are age 37. They have six-year-old twins and a ten year-old. The couple's limited resources place them in the bottom resource quintile. Their massive LMTR – 652.9 percent – primarily reflects the loss of SNAP benefits from earning the posited extra $1,000. Idaho has three SNAP eligibility tests – one on gross income, one on net income, and one on assets. The 2023 gross income eligibility threshold for SNAP in Idaho is 130 percent of the Federal Poverty Level (FPL), the net income eligibility threshold is 100 percent of the FPL, and the asset test is just $5,000.[10] Clearly, earning even a bit too much can eliminate all SNAP benefits in the current year. And those benefits can be considerable: In 2023, the family's *monthly* SNAP benefit was $1,116.[11] Since the couple doesn't exceed the SNAP threshold in future years, their CMTR of 817.7 percent exceeds their 652.9 percent LMTR.

Table 2: Breakdown of LMTR and CMTR sources, Case II

	C Baseline	C Marginal	C Diff	L Baseline	L Marginal	L Diff
Federal Income Tax	2,844	3,026	182	91,864	91,503	-361
State Income Tax	3,002	3,073	71	48,398	48,125	-273
Other Taxes	5,925	5,964	39	93,791	93,210	-581
Total Taxes	11,770	12,062	292	234,054	232,839	-1,215
SNAP	6,489	0	-6,489	12,652	6,285	-6,367
TANF	0	0	0	0	0	0
Section 8	0	0	0	0	0	0
CCDF	0	0	0	0	0	0
Social Security	0	0	0	67,723	67,742	19
SSI	0	0	0	0	0	0
Mcare	0	0	0	39,689	39,689	0
Mcaid	8,125	8,125	0	67,872	67,872	0
ACA	0	0	0	0	0	0
Other Transfers	1,396	0	-1,396	5,360	3,964	-1,396
Total Transfer Payments	16,010	8,125	-7,885	193,297	185,553	-7,744
Net Taxes	**-4,240**	**3,937**	**8,177**	**40,757**	**47,286**	**6,529**

Note: All numbers are calculated based on a $1,000 increase in current-year earnings. Weighted Mean values are presented.

Were this household to participate in all eligible programs, their LMTR would actually *fall* to 40.4 percent. The reason is that their lifetime SNAP benefit would fall from $12,652 to only $254. Why? Because they would, under our supposition, partake in Section 8 housing assistance and child care subsidy payments provided by the Child Care Development Fund (CCDF), which provides childcare assistance.[12]

Participating in these programs significantly reduces available SNAP benefits and, thus, the size of the potential loss of these benefits from additional earnings. To be clear, the couple's

[9]State sales and federal excise taxes constitute implicit labor-income taxation since they curtail the ability to consume per dollar earned. The effective labor-income tax rate is $1 - 1/(1.079)$ or 7.3 percent.

[10]https://www.fns.usda.gov/snap/broad-based-categorical-eligibility

[11]https://fns-prod.azureedge.us/sites/default/files/resource-files/snap-fy-2023-cola-adjustments.pdf

[12]Note that the CCDF is distinct from the Child and Dependent Care Tax Credit (CDCTC). Our study incorporates federal and state child tax credits (CTCs) in addition to the CCDF. However, it does not include the CDCTC as it requires childcare expense data, which is not reported in the SCF.

652.9 percent LMTR under partial participation arises in part from the loss of other benefits besides SNAP.

2.3 Case III

This case illustrates the potential for negative LMTRs to coincide with positive CMTRs. It features a bottom-quintile Ohio couple whose spouses are ages 40 and 42. The couple's CMTR is 36.9 percent, produced by an increase in taxes of 14.6 cents and a loss of SNAP benefits of 22.3 cents per dollar of extra earnings. But their LMTR is -336.7 percent! This significantly negative rate is almost entirely due to the couple becoming eligible for additional SSI benefits. The reason for this is subtle. In earning more, the couple loses current-year benefits. Consequently, they save less. But this also makes them eligible for more SSI benefits – $80 to $200 more per year – for every year after they retire. As table 3 shows, the net present value decrease in lifetime net taxes due to the increase in SSI benefits is $3,367.

Table 3: Breakdown of LMTR and CMTR sources, Case III

	C Baseline	C Marginal	C Diff	L Baseline	L Marginal	L Diff
Federal Income Tax	-467	-396	71	36,222	36,310	88
State Income Tax	133	133	0	2,162	2,164	2
Other Taxes	2,952	3,027	75	47,844	47,764	-80
Total Taxes	2,617	2,763	146	86,227	86,237	10
SNAP	2,152	1,929	-223	10,054	9,969	-85
TANF	0	0	0	0	0	0
Section 8	0	0	0	0	0	0
CCDF	0	0	0	0	0	0
Social Security	0	0	0	61,435	61,452	17
SSI	0	0	0	4,201	7,561	3,360
Medicare	0	0	0	46,118	46,118	0
Medicaid	22,590	22,590	0	203,075	203,160	85
ACA	0	0	0	0	0	0
Other Transfers	1,869	1,869	0	32,616	32,616	0
Total Transfer Payments	26,612	26,389	-223	357,499	360,876	3,377
Net Taxes	**-23,995**	**-23,626**	**369**	**-271,272**	**-274,639**	**-3,367**

Note: All numbers are calculated based on a $1,000 increase in current-year earnings. Weighted Mean values are presented.

3 Prior Studies

Prior studies use a variety of methods and data sources to form CMTR measures. Joines (1981) is an early example. Joines uses IRS data to compute weighted-average marginal tax rates on labor and capital income over the years 1929 through 1975. His estimates assume proportional and nonproportional rate schedules for various federal, state, and local tax liabilities. Nonproportional rates on capital are estimated from changes in average personal-income tax payments associated with aggregated adjusted gross income classes reported in the *Statistics of Income*. Nonproportional effective rates on labor are derived similarly, with the addition of weighted average calculations for combined employer-employee and self-employed Social Security tax rates derived from statutory rate schedules. An aggregate measure of the effective marginal tax rates is obtained from these estimates by adding all other taxes – sales taxes, corporate income taxes, and property – which are assumed to be proportional.

Seater (1982) and especially Seater (1985) take a similar approach, though without the detailed breakdown by source of income, and only focusing on federal taxation. Barro and Sahasakul (1986) point out that actual tax payments incorporate endogenous behavioral responses, including changes in work and saving as well as tax avoidance and evasion. To control for such responses, they simply measure marginal tax rates using federal tax-rate schedules. Average marginal tax rates are derived by weighting the marginal rates applicable to each AGI class by either the income shares or return shares that they represent. Unlike Joines (1981), but as in Seater (1985), Barro and Sahasakul (1986) consider only the federal personal income tax and Social Security.

Given the heterogenity in LMTRs and CMTRs reported here, Barro and Sahasakul's reliance on bracket values to estimate marginal tax rates is problematic on other grounds as well. The approach ignores a range of provisions that render the "full" marginal tax rate schedule substantially different from the statutory schedule. Examples include the taxation of first, up to half, and then, up to 85 percent, of Social Security benefits beyond two nominal thresholds, the earnings-dependent provision and clawback of the Earned Income Tax Credit (EITC), not to mention ever changing floors and ceilings on various income tax deductions, such as medical expenses and charitable contributions.

Several studies have focused on characterizing actual effective, as opposed to statutory, tax rates. Barthold et al. (1998), for example, show how considering 22 such income tax provisions impacted effective federal marginal income taxation in 1988. Along the same vein, Feenberg and Poterba (2004) analyze the importance of the Alternative Minimum Tax and how marginal tax rates have been affected by its reform. Guner et al. (2014) exploit 2000 IRS public use files to estimate effective tax functions by incorporating multiple deductions and adjustments to reported income.

None one of these studies include transfer payments – a serious omission. Moffitt (1992) provides a comprehensive review of the incentive effects of the U.S. welfare system. Shaviro (1999) stresses the need to include negative benefit programs. He estimated current-year marginal net tax rates for representative low-income individuals incorporating Tax Assistance for Needy Families (TANF), housing assistance, Medicaid, and the Supplemental Nutrition Assistance Program (SNAP). Shaviro showed that income-induced benefit losses can be far more important to marginal net taxation than tax-side provisions. Borella et al. (2023) estimate marginal tax rates and the dynamic impact of tax reform on labor supply, inclusive of transfer payments. Their methodology relies on estimating the parameters of a simplified tax function by regressing measures of post-tax income (inclusive of transfers) on pre-tax income obtained from observations in the Panel Study on Income Dynamics. Focusing on changes in tax regimes over time, they find meaningful effects on labor supply on both intensive and extensive margins.

The U.S. Department of Health and Human Services (HHS) has, of late, begun estimating CMTRs incorporating key tax and transfer programs. HHS uses data from the Current Population Survey and the Urban Institute's Transfer Income Model, Version 3 (TRIM3).[13]

Another recent study by the Congressional Budget Office 2015 considers the level and dispersion of marginal tax rates taking into account state income taxes and federal taxes as well as two important benefit programs – SNAP and subsidies provided by the ACA. This study finds high median as well as dispersed CMTRs for those with incomes between 100 percent and 150 percent of the federal poverty line. Kosar and Moffitt (2017) take a similar approach, but consider more benefit programs, including housing subsidies and TANF, and incorporate take-up rates. They also entertain valuation discounts associated with in-kind benefits (housing and health care programs). Similar to the CBO, Kosar and Moffitt find more dispersed and higher median marginal

[13]See, for example, Giannrelli et al. (2019) and Macartney and Chien (2019). HHS CMTR project's website is https://aspe.hhs.gov/marginal-tax-rate-series. The analysis models a large set of public assistance programs including TANF, SNAP, CCDF child care subsidies, housing assistance, Medicaid/CHIP, Women Infants and Children (WIC), Low Income Heating and Energy Assistance Program (LIHEAP), and unemployment insurance.

tax rates among those just above the FPL. However, they estimate that the problem of very high marginal tax rates among the poor, including rates exceeding 100 percent, is concentrated among a relatively small share of the eligible population who actually participate in more than two of the benefit programs they consider. [14]

Gokhale et al. (2002) and Kotlikoff and Rapson (2007) come closest to our study. They used an early version of our computation engine to make LMTR calculations and, in the case of Kotlikoff and Rapson (2007), also measure the lifetime marginal net tax on saving. However, both studies consider only a small set of stylized households assumed to live in Massachusetts. Kotlikoff and Rapson (2007) incorporates actuarial valuation, but not the dependency of survival rates on income included here. Neither paper handles our range of transfer programs, nor considers benefit-program take up. Although the two papers anticipate many of the general conclusions reached here, their failure to process actual data precludes understanding central tendencies and dispersion in the distributions, across and within resource level, of LMTRs and CMTRs. This also holds for comparisons of marginal net tax rates over time. That said, the two studies represent critical foundational exercises for our analysis, breaking new ground in conceptualizing and calculating comprehensive average and marginal *lifetime* rates of net taxation.

4 Our Remaining Lifetime Framework

Consider any potential survival path, i. Along that path, the realized present value of total remaining lifetime spending – discretionary plus non-discretionary spending, including in-kind healthcare transfers, imputed rent on home ownership, and bequests (home equity and financial), denoted by S_i, must equal the realized present value of lifetime net resources. i.e., the intertemporal budget must be satisfied.

$$S_i = R_i - T_i, \tag{1}$$

where R_i and T_i reference, respectively, the realized present values, on path i, of the household's remaining lifetime resources and net taxes (including estate taxes), respectively. The realized present value of remaining lifetime resources, R_i, is the sum of the household's current net wealth, W, and path $i's$ human wealth – the realized, along path i of the present value of remaining future labor earnings, H_i. i.e.,

$$R_i = W + H_i. \tag{2}$$

The expected remaining lifetime present values of spending, both discretionary and non discretionary, S, labor earnings, H, resources, R, and lifetime net taxes, T, satisfy

$$S = \sum_i p_i S_i, \tag{3}$$

$$H = \sum_i p_i H_i, \tag{4}$$

$$T = \sum_i p_i T_i, \tag{5}$$

and

$$R = \sum_i p_i R_i, \tag{6}$$

[14] Fleck et al. (2021) is another salient study that incorporates an extensive set of transfer payments in the calculation of rates. Their emphasis is on differences in the progressivity of tax rates across states. We discuss their work in more detail in section 9 where we take up state-by-state variation.

where p_i is the probability the household experiences survival path i. The above equations imply

$$R = W + H, \tag{7}$$

$$S = R - T, \tag{8}$$

and

$$LMTR = \frac{\Delta T}{\Delta R}. \tag{9}$$

Since LMTR incorporates future as well as current net taxes, it will differ from the analogous current-year calculation, CMTR. CMTR is given by

$$CMTR = \frac{\Delta T_t}{\Delta R_t}, \tag{10}$$

where T_t references current-year net tax payments.

Since T and ΔT differ across households of different ages for purely life-cycle reasons, LMTR will depend on the household's age as well as its position in the lifetime-resource distribution. Consequently, we present most of our results on a cohort- and resource-specific basis. Our baseline calculation of LMTR incorporates additional current as well as future net taxes from earning an extra \$1,000. Specifically, we measure the amount by which an extra \$1,000 in current, pre-tax labor earnings raises our SCF-respondents' present values of expected remaining lifetime net taxes.[15] As for the current-year marginal net tax rate, we simply form the ratio of additional current-year net taxes to \$1,000.[16]

4.1 Measuring Lifetime Discretionary Spending

Our goal is to measure earnings-induced changes in S – the sum of expected discretionary and non-discretionary annual spending along each survivor path. Annual non-discretionary spending on each survivor path is computed/imputed based on our SCF data and ancillary assumptions, such as the retention of owner-occupied housing. It includes in-kind consumption transfers, such as Medicare and Medicaid benefits, plus actual or imputed rent on housing plus terminal home equity and financial bequests.[17]

But how do we calculate survivor-path-specific annual discretionary spending? First, we posit a relationship between annual discretionary spending and living standard per adult-equivalent household member. Second, we adopt the standard model of lifetime utility maximization under lifespan uncertainty, namely Yaari (1965). This seminal paper indicates that households will smooth their consumption (living standard in our context) subject to borrowing constraints taking maximum longevity – the latest year to which a head or spouse/partner could survive – as the planning horizon. As indicated, this max longevity case is central to TFA's calculations as it determines survivor living standard paths to be protected, via life insurance, in the case of early deaths of heads or spouse/partners. Our calculations take age 100 as each SCF's respondent's maximum lifespan.

[15]As the above equations indicate, the term "expected" refers to the weighted average of the present value of additional lifetime net taxes along each household's possible future survivor path, where the weight references the probability of the particular survivor path in question.

[16]Section 10 presents sensitivity analyses using alternate income amount of \$100 and \$10,000.

[17]The expected present value of non-discretionary spending is added to that of discretionary spending in forming S.

Our assumed relationship between a household's discretionary spending in year t, C_t, and its underlying living standard per effective adult, c_t, is given by

$$C_t = c_t(N + .7K)^{.642}, \tag{11}$$

where N stands for the number of adults in the household and K for the number of children. The coefficient .642 is chosen such that 2 adults can live as cheaply, with respect to discretionary spending, as 1.6 adults living by themselves.[18] Clearly, a single household's living standard in a given year is simply its discretionary spending. In the case of an early (before age 100) death of a head or spouse/partner, the path of c_t calculated under max longevity coupled with the above formula, setting N equal either to 1 or, for singles, 0, indicates the annual discretionary spending needed by survivors, in this case young or disabled children, to maintain their living standard. This, in turn, indicates the additional resources required in the form of life insurance. Life insurance is set to zero if survivors can sustain a higher than max-longevity living-standard path.

5 The Fiscal Analyzer

The Fiscal Analyzer (TFA), developed in Auerbach et al. (2017), Altig et al. (2020), Auerbach et al. (2023), and Altig et al. (2024), is a life-cycle, consumption-smoothing tool that incorporates cash flow (borrowing) constraints and all major federal and state fiscal policies. These policies are listed in table 4.[19]

To abstract from preferences, TFA assumes that households seek to perfectly smooth their living standards to the extent possible without borrowing or, if already indebted, additional borrowing. Note that TFA can accommodate any desired age-living-standard profile. Our assumption of a preferred perfectly smooth profile as opposed to one that, for example, gradually declines after age 75 does not materially alter our results.[20] Although we target perfect consumption smoothing, households' age-discretionary expenditure profiles, along given survival paths, typically vary substantially as the household's demographic composition changes due to the departure of children and emergence from a borrowing-constrained interval. Figure A1 in Auerbach et al. (2023) shows that the average living standard profile across our SCF sample rises fairly steadily with age. This reflects the large share of the sample, 68.2 percent, that is subject to one or more cash-flow constrained intervals as they age. TFA's algorithm treats non-discretionary

[18] OECD (2013) discusses OECD equivalency scales. The "old" scale treated each additional adult as 70 percent as expensive and each additional child as 50 percent as expensive as a single adult. The "OECD-modified equivalence scale" treats each additional adult as 50 percent and each child as 30 percent as expensive as a single adult. A third OECD scale divides household income by the square root of the number of household members. In comparing single versus married households, our scale splits the difference between the old and modified OECD scales, but it provides for increased economies with the number of household members.

[19] We assume that all tax and transfer policies follow current legislation, including specified future reversions of aspects of the 2017 Tax Cuts and Jobs Act (TCJA) to pre-TCJA provisions. We also assume that all tax and transfer policies, specifically eligibility rules, thresholds, brackets, and schedules, are or are not adjusted through time, to inflation and economy-wide wage growth in accord with explicit legislation or general practice. Examples are the lagged indexation of federal income tax brackets based on the C-CPI, the non-indexation of thresholds governing Social Security benefit taxation, the lagged indexation of Social Security benefits to the CPI, and the indexation through age 60 of workers' past covered earnings to the economy's Average Wage Index. Altig et al. (2024) as well as Auerbach et al. (2023) provide a full description of our procedures.

[20] Assuming a 1 percentage point per year reduction in desired standard of living starting from age 75 reduces the median LMTR by just 1.4 percentage point.

outlays as given. The latter comprises housing expenses, including direct expenses, bequests of housing equity, and foregone interest, special expenses, and endogenously computed net taxes.

Table 4: List of Tax and Transfer Programs Included in TFA

Taxes	Personal Income Tax (federal and state) Corporate Income Tax (federal and state) FICA Tax (federal) Sales Taxes (state) Medicare Part B Premiums (federal) Estate and Gift Tax (federal)
Transfer Programs	Earned Income Tax Credit (federal and state) Child Tax Credit (federal) Social Security Benefits (federal) Supplemental Security Income (SSI) (federal) Supplemental Nutritional Assistance Program (SNAP) (federal and state) Temporary Assistance for Needy Families (TANF) (federal and state) Medicaid (federal and state) Medicare (federal) The Affordable Care Act (ACA) (federal and state) Section 8 Housing Vouchers (state and county) Energy Assistance (state) Childcare Assistance (state and county)

Note: Section 8 Housing benefits and Childcare Assistance are also county specific. ACA subsidies are also zip-code specific. TFA lacks data on county or zip codes needed to calculate benefits based on county or zip code.

5.1 TFA's SCF and Imputed Inputs

TFA's SCF-available data include marital status, birth dates of each spouse/partner, birth dates of children, current-year labor earnings, current regular, Roth, and non-Roth retirement account asset balances, retirement-account contributions, housing expenses, real estate holdings, household debts, and defined benefit pensions. Imputed data include past and future labor earnings, workers' retirement ages, welfare and benefit program take up, and state of residence. We also provide TFA with the observed post-war pre-tax real return on national wealth, an assumed inflation rate, a Social Security benefit collection age (taken as the age of retirement), and a retirement-account withdrawal start date.

5.2 TFA's Solution Method

TFA's problem is to jointly determine survivor-specific realized paths of discretionary spending. Each such path must satisfy the household's realized lifetime budget, respect cash flow constraints, and provide the same (when life insurance is required) or higher (when life insurance is not required) living standard path for survivors as they would experience in the max-longevity case. The program must also simultaneously calculate annual net taxes along each survivor path as well as non-negative values of life insurance that the household purchases at each age along its max-longevity path. When positive, these life insurance amounts suffice to provide survivors with sufficient resources to sustain the max-longevity living standard path through the household's last possible year.

This problem is computationally daunting for four reasons. First, there is the curse of dimensionality arising from the tens of thousands of survivor-path-specific state assets. These are the levels of regular as well as head- and spouse/partner-specific tax-deferred and Roth retirement accounts in each survivor state.[21] Second, taxes and benefit payments, discretionary spending, and life insurance holdings must be separately determined for all years along all potential survivor paths. Third, spending, insurance amounts, and net taxes are interdependent along any given survivor path as well as across survivor paths. Hence, one needs a simultaneous equations solution. Fourth, the presence of cash-flow constraints introduces major interpolation error to the standard consumption-smoothing dynamic program. Consumption (living standard) functions become non-differentiable with interpolation error compounding as one programs backwards.

TFA uses iterative dynamic programming - see Economic Security Planning, Inc.'s (ESP) patent #US6611807B1. ESP's main commercial product is its lifetime economics-based financial planning tool called MaxiFi Planner. TFA shares MaxiFi Planner's computation engine.[22] TFA's algorithm iterates between three dynamic programs. The first smooths the household's living standard along its maximum longevity path. The second determines annual life insurance needs for each possible death date of the household head and, if present, spouse/partner, while jointly calculating future annual net taxes along all potential survivor paths. The third determines annual net taxes along the max-longevity path.

The max-longevity, living standard-smoothing program takes the household's future labor earnings, annual life insurance premiums, housing and other special expenses, and net taxes (along this survival path) as given.[23] It then formulates, via backward induction, living standard functions of the state vector – household regular assets plus Roth and non-Roth retirement accounts of the head and, for non singles, spouse/partner.[24] The induction equalizes the household's living standard across years subject to annual cash-flow constraints.

Given the household's computed year-specific discretionary spending functions, we project the household's living-standard path forward based on current-year initial asset holdings. The second dynamic program takes the household's max-longevity projected living-standard path and calculates the household head- and spouse/partner-specific term life insurance amounts needed to provide all survivors with the same living standard as they would experience in the max-longevity scenario. This routine incorporates the need to sustain the living standards of children through age 19 and disabled children through the household's last potential year of survival.[25] It also calculates the annual net taxes survivors will pay.[26]

The third program takes the first program's discretionary spending and associated asset and

[21]Consider a 40 year-old couple that could live to 100. They have 200,000 survivor contingent regular and retirement account state variables, such as the regular, tax-deferred and Roth retirement account assets of a 69 year-old widow if her husband dies at age 51.

[22]Note, MaxiFi Planner is available for use by academics upon request and subject to an NDA. To date, more than a dozen economists (two foreign) in academe and the Federal Reserve have used TFA for research, including modifying its source code as needed.

[23]Property taxes are treated as payment for local amenities, not a work disincentive. Current housing choices are assumed to remain fixed through time. Hence, homeowners bequeath their homes when the last survivor passes. Special expenses include alimony payments, repayments of car loans and personal debts.

[24]The retirement account elements of the state vector along each survivor path are predetermined given initial conditions, our projection of contributions, and the assumption that married/partnered decedents bequeath their accounts to their spouse/partner.

[25]There is also an inner loop determining how much life insurance surviving spouses/partners need to protect young or adult disabled children. The premium that will be paid by such survivors helps determine how much life insurance the potential decedent spouse/partner needs to purchase. I.e., TFA accounts for the simultaneity between the life insurance needs of a potential decendant and those of a surviving spouse/partner.

[26]TFA assumes that survivors are not subject to cash flow constraints. But, after convergence, it runs separate dynamic programs for all potential survivor households, which impose cash flow constraints, grid shrinking, and outer-loop updating of net tax paths. These post-processing runs incorporate the life insurance survivors will receive as determined in the main routine.

asset-income paths, which, indirectly, depend on the max-longevity life insurance premium path, as given and calculates annual net taxes along the maximum longevity path. To be clear, this outer-loop routine calculates each year's federal and, if relevant, state income taxes, FICA taxes, and IRMAA premiums as well as available benefits based on all relevant tax and benefit eligibility provisions and schedules.[27] Thus, each program, either directly or indirectly, takes the output of the other programs as inputs with the iteration proceeding to convergence. Convergence entails lifetime present-value budget balance within one dollar.

TFA overcomes the aforementioned non-differentiability/interpolation error problem using a proprietary sparse grid method.

5.3 The Max-Longevity Dynamic Program

This section formally describes the first of TFA's three routines. Consider the simplest case of a single worker in year 0 who will live, at most, to year T. The worker saves and invests in regular (non retirement-account) assets and has no off-the-top expenses. By assumption, the agent smooths her annual living standard – consumption – across all future years to which she might survive subject to annual cash-flow constraints. Consumption in T satisfies

$$C_T = A_T(1+R) + E_T - X_T, \tag{12}$$

where A_T is beginning of time-T regular assets, R is the pre-tax real return, E_T is the agent's labor earnings, and X_T is time-T net taxes. For year $t < T$, set

$$C_{t-1} = C_t(A_t) \quad \text{if} \quad A_t > 0, \tag{13}$$

where $A_t = A_{t-1}(1+R) - C_{T-1} + E_{t-1} - X_{t-1}$. Otherwise, set

$$C_{t-1} = A_{t-1}(1+R) + E_{t-1} - X_{t-1}. \tag{14}$$

Next, suppose the household is married with children. In this case, our consumption-smoothing routine equalizes c_t, the household's living standard per equivalent adult, across time subject to annual cash flow constraints.[28] The relationship between C_t and c_t is given above.

5.4 Confirming TFA's Solutions

Although TFA's internal workings are complex, its algorithm can be confirmed in six ways. First, the realized present-value lifetime budget constraints of each household are satisfied to many decimal places along all survival paths. These constraints take into account spending in the form of terminal bequests of both regular and retirement account assets less estate taxes and funeral expenses. Second, each unconstrained household's living standard is smoothed to the real dollar across all future years. Third, for households that are constrained for one or more years, the living standard is smoothed within each constrained interval. Furthermore, the living standard is always higher in constrained intervals that occur later in time. Fourth, regular assets

[27]The alternative to this outer-loop method is time-consuming, grid-point-specific inner loop calls to the TFA's net tax subroutine in the max-longevity dynamic program.

[28]TFA can, as here, be run assuming zero borrowing or with an arbitrarily permitted level of borrowing. Our algorithm is modified to limit asset tests in the case that saving in year t would lead to less cash on hand because more benefits are lost by saving. In these cases we assume that such workers either hide their saving, by, for example, parking it with a relative or simply increase their immediate spending on, for example, durables.

in the year before a borrowing constraint is lifted (via, for example, termination of mortgage payments) are zero.[29] Fifth, if a spouse/partner dies having purchased, the year before, TFA's recommended term life insurance, the living standard path of survivors through their maximum ages of life (in the case of spouse/partners) and through their leaving the household (in the case of children) is, to the dollar, identical to what they would otherwise had both the head and spouse/partner lived to their maximum ages of life. Sixth, the household's regular assets are less than TFA is told the household can borrow.[30]

6 Data, Benchmarking, Imputations, and Adjustments

The SCF is a cross-section survey conducted every three years. The survey over-samples wealthy households in the process of collecting data from, in the case of the 2019 Survey, 5,777 households.[31] These data include detailed information on household labor and asset income, assets and liabilities, and demographic characteristics.[32] For all subsequent imputations and adjustments, we assume that each SCF primary economic unit (PEU), including reported dependents, comprise a single tax unit.[33]

Survey household-weighted totals of various economic and fiscal aggregates differ from their direct counterparts in the National Income and Product Account (NIPA) and Federal Reserve Financial Accounts (FA). To assure concordance, we follow Dettling et al. (2015) and set SCF benchmark factors to ensure that SCF-weighted aggregates precisely coincide with conceptually comparable NIPA and FA aggregates.[34] Running the TFA also requires seven imputations and adjustments to provide inputs not available from the SCF.[35] We summarize our methods here referring readers to Appendix sections A1.2 through A1.8 for details.

First, state identifiers are needed to calculate state-specific taxes and transfer payments. The reason? The public-use SCF release does not provide state identifiers.[36] Hence, we allocate SCF households to different states based on the 2019 American Community Survey using the approach in Altig et al. (2020). Specifically, we impute state residency based on a statistical

[29]This is a requirement of constrained consumption smoothing. Bringing positive assets into years when the living standard is higher is inconsistent with consumption smoothing, which minimizes living standard discrepancies to the maximum extent consistent with the household's borrowing constraint.

[30]MaxiFi Planner is available for free to academics by contacting Laurence Kotlikoff. Anyone running this commercial version of TFA can readily confirm each of the above solution properties.

[31]The SCF combines an area-probability sample of households with a "list" sample of generally wealthier households from administrative tax records from the IRS. The SCF includes sampling weights to account for oversampling of wealthier households from inclusion of the "list" sample and for differential response rates among wealthier groups. Wealthier households have lower response rates, particularly at the highest levels (Bricker et al. 2016). The oversampling of wealthy households allows for inference about households in the top 1 percent of the resource distribution. For the 2004 SCF, Kennickell (2007) shows that 15.8 percent of sampled households were in the top 1 percent of the net worth distribution for the U.S. with 96.4 percent of these coming from the list sample. Another 38.5 percent of the 2004 SCF-sampled households were in the bottom 50 percent of the distribution, with only 5.7 percent of these households coming from the list sample.

[32]Using a multiple imputation algorithm, the Fed includes each household's record in the public-use SCF dataset in five so-called replicates to account for estimation of non-reported values (item non-response) or for disclosure limitations. We use the first replicate for our analysis. Auerbach et al. (2017, 2023) report no significant differences in results across replicates.

[33]SCF also records data on financially independent adults outside the PEU, which are not used in calculations.

[34]See Appendix section A1.1 for details.

[35]Most of the imputations and adjustments are described in detail in our other papers.

[36]The Federal Reserve's data set does include state indentifiers, but not state-specific weights.

match to the American Community Survey (ACS) and assign each SCF household to each state (plus the District of Columbia) such that the sum of each households state-specific weight equals its SCF weight. Second, TFA needs future earnings to calculate resources along survival paths and past and future covered earnings to calculate Social Security benefits. Following Auerbach et al. (2023), we use CPS data to backcast and forecast each SCF respondent's past and future earnings through retirement.

Third, SCF respondents do not all respond to questions about retirement and those that do appear to be overly optimistic about their ability to continue working. Here we follow Altig et al. (2022) and use the 2019 ACS to impute age- and demographic-specific retirement hazards. Fourth, the SCF provides limited information about public-assistance program take-up. To match nationally reported participation rates, we use the TFA to directly calculate eligibility and combine SCF data with observations from the Annual Social and Economic Supplement (ASEC) and other sources to probabilistically infer household- and program-specific take-up (Ilin and Terry 2021). The full approach is detailed in Appendix A1.5.

Fifth, TFA requires assumptions about pre-tax, real and nominal rates of return on assets held by households. Following Auerbach et al. (2023), we set the real rate of return to the average return on national wealth between 1948 and 2018 as estimated by NIPA. We assume an inflation rate of 2 percent. Sixth, TFA requires survival-path probabilities, which we construct from mortality rate estimated by the Committee on the Long-Run Macroeconomic Effects of the Aging US Population (2015). Finally, TFA requires precise inflation indexation of federal and state taxes, Social Security benefits, and Medicare and Medicaid benefits. These adjustments are implemented per Altig et al. (2024).

7 Results

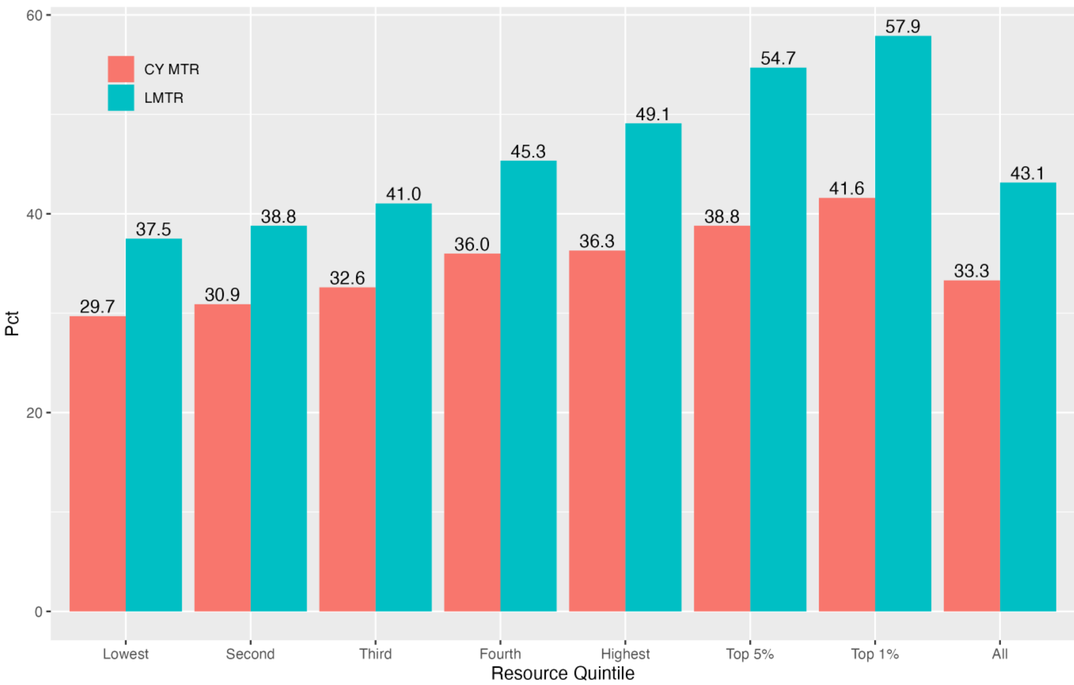
7.1 Aggregate Results

We now turn to the distribution of results in the aggregate. For all subsequent results, we restrict the sample to households age 20 to 69 where the head and spouse (if applicable) are not both retired or disabled. Figure 1 shows median marginal tax rates for all age groups by their age-group specific lifetime-resource quintile, where lifetime resources equal initial wealth plus the present expected (over survival paths) value of future labor income – resources that would, on average, be available for consumption in the absence of taxes and transfers. Both measures are calculated based on a $1,000 increase in current-year earnings. For the overall population, the median LMTR is 9.8 percentage points higher than the median CMTR – 43.1 versus 33.3 percent. This revealed impact of double taxation is particularly striking for the top 1 percent. For this group, the median LMTR is 57.9 percent – considerably higher than the corresponding median CMTR of 41.6 percent.

These overall findings are significantly affected by our use of actual take-up rates of benefits in calculating marginal tax rates. Had we instead assumed full take-up based on eligibility, this would have resulted in substantially higher tax rates at the bottom of the resource distribution, as figure 2 shows. For the bottom quintile, the median LMTR would be 48.8 percent rather than 37.5 percent. As shown in figure A2, the median CMTR would be 40.3 percent rather than 29.7 percent. As expected, the welfare take-up assumption has virtually no impact on middle- and high-income households in the top three resource quintiles.

Under the full take-up assumption, we observed a clear U-shaped pattern for both LMTRs and CMTRs as suggested by Diamond (1998) and Saez (2001). However, this pattern disappears assuming realistic take-up. Exceptionally high LMTRs and CMTRs are often a product of

Figure 1: Median Lifetime and Current-Year MTR, Ages 20-69



households losing multiple benefits simultaneously when receiving additional income. Under realistic participation, such households are relatively rare, lowering median rates of the bottom quintiles to below those of the middle and upper quintiles.

7.2 Median Marginal Tax Rates by Age-Resource Quintiles

Figures A3 - A7 present age-cohort-specific LMTR and CMTR values broken down by lifetime-resource quintiles. Median values of CMTR are substantially lower than their LMTR counterparts for all cohorts. However, there are important cohort-specific differences. LMTRs don't vary much by resource group for those between 20 and 29, with the maximum difference in median LMTR across resource quintiles being only 7.6 percent. At higher ages, this pattern gradually disappears, as lifetime tax rates rise more rapidly across resource groups. For 50 to 59 year-olds, the maximum difference across resource quintiles is 16.6 percent.

7.3 Distribution of Lifetime Marginal Net Tax Rates

Figures 3 and A8 plot distributions of LMTR and CMTR, respectively. There is major dispersion in work disincentives at all resource levels.[37] But whether one considers LMTR or CMTR, the dispersion is dramatic at the bottom of the resource distribution. As shown in table 5, many households face extremely high lifetime marginal tax rates exceeding 100 percent. Among those in the bottom resource quintile, approximately one in ten households face lifetime rates above 70 percent. One in four bottom-quintile households face CMTRs above 40 percent, higher than the median rate of 38.8 percent experienced by households among the top 5 percent.

[37]There is overlap in lifetime resource quintiles because we assign quintiles within each age cohort (e.g. 30-39 year-olds). Therefore, a younger household in a lower resource quintile may have more lifetime resources than an older households in a higher quintile.

Figure 2: Median Lifetime MTR By Welfare Participation Assumption, Ages 20-69

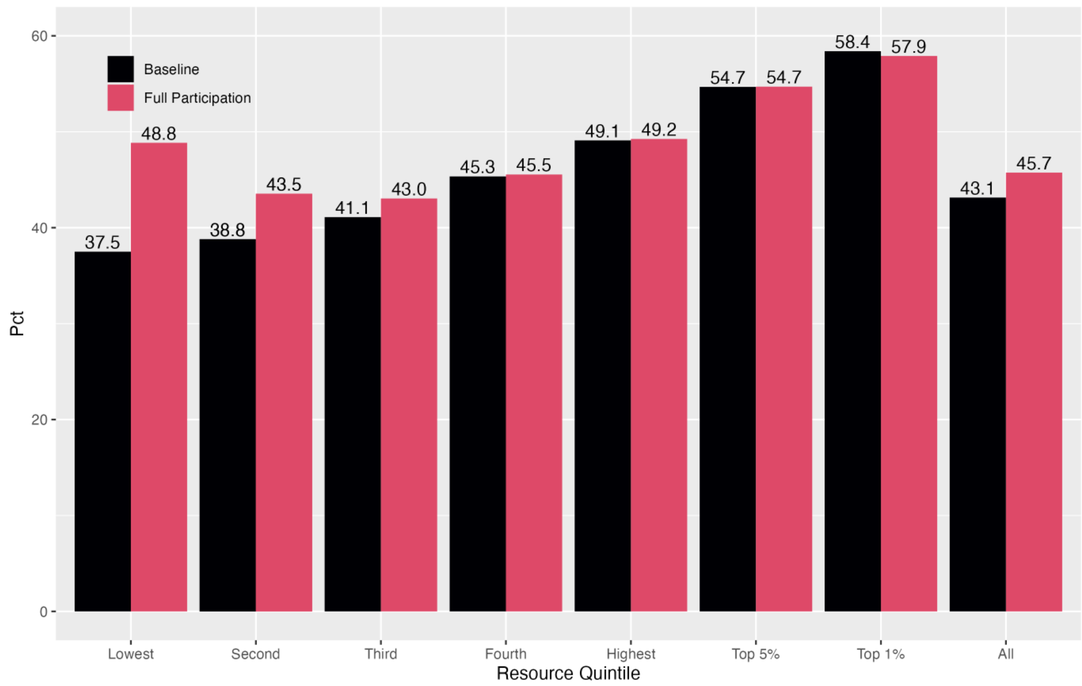


Figure 3: LMTR from $1,000 Earnings Increase in Current Year, Ages 20-69

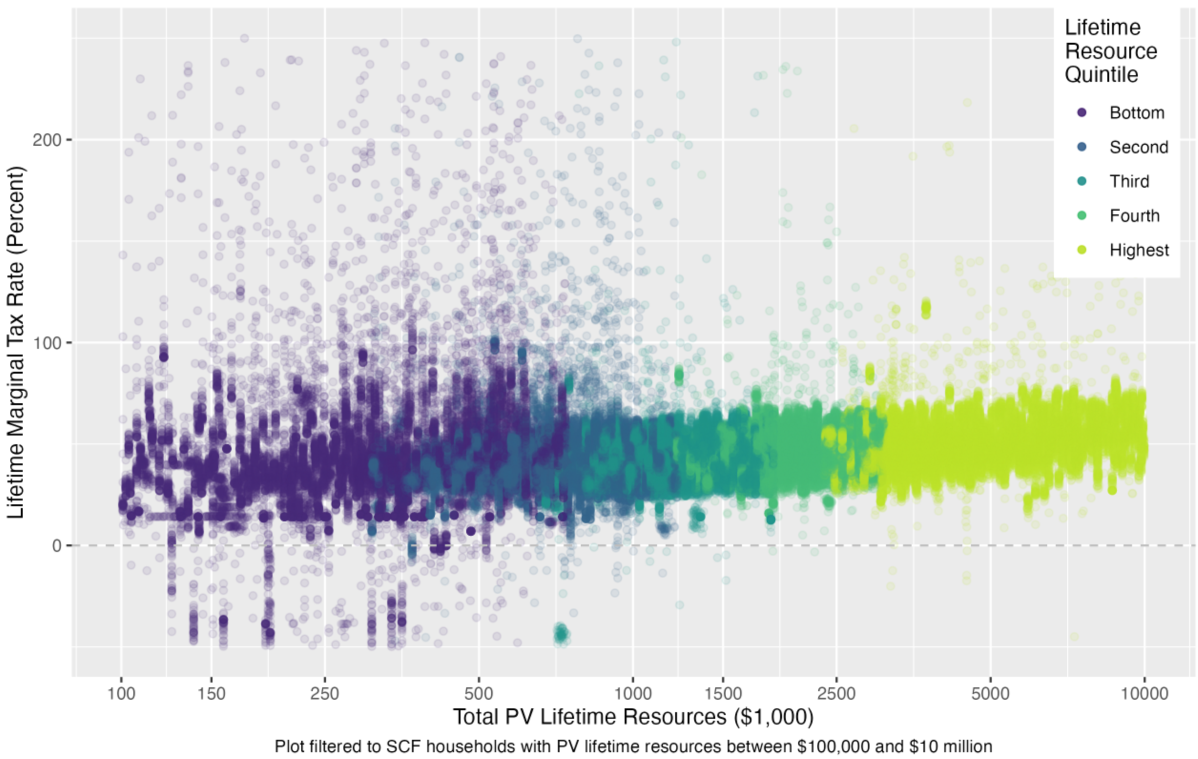


Table 5: Summary of Marginal Tax Rates, Age 20-69, Imputed Participation

Lifetime Marginal Tax Rates

Resource Group	q25	median	mean	q75	q90	std.dev
Bottom	25.3	37.5	43.3	49.7	69.8	439.5
Second	32.7	38.8	44.0	46.8	54.9	106.1
Third	34.2	41.0	41.4	48.5	54.7	33.2
Fourth	40.1	45.3	46.1	52.4	57.9	10.7
Highest	42.8	49.1	50.2	57.2	64.2	17.0
Top 5%	46.7	54.7	54.2	61.7	67.5	20.3
Top 1%	49.9	57.9	55.8	65.0	69.8	13.9
All	34.9	43.1	45.0	51.5	59.7	185.5

Current-Year Marginal Tax Rates

Resource Group	q25	median	mean	q75	q90	std.dev
Bottom	22.4	29.7	35.6	40.4	58.8	104.0
Second	28.0	30.9	40.0	38.0	44.5	67.2
Third	29.2	32.6	33.5	37.9	40.5	18.1
Fourth	31.0	36.0	35.3	39.6	41.8	11.2
Highest	30.0	36.3	35.8	40.9	44.3	8.6
Top 5%	33.6	38.8	38.4	43.1	47.8	8.4
Top 1%	37.3	41.6	40.8	45.2	50.1	8.7
All	28.4	33.3	36.0	39.4	43.6	51.2

Figures A9, A10, and table A6 repeat figure 3, figure A8 and table 5, but assumes full welfare program participation. For the subset of households who do partake in all welfare programs, work disincentives are far more severe. Indeed, for the bottom quintile, 21.1 percent of LMTR values in figure A9 and 15 percent of CMTR values in figure A10 values exceed 75 percent.[38] A 75 percent or higher marginal tax rate surely suffices to lock affected households out of the workforce.

These full participation results are important for two reasons. First, they show the potential full extent of the poverty lock underlying the design of the U.S. federal and state tax and transfer systems. Second, they indicate that, absent reform that lowers work disincentives program by program or via an end-of-year adjustment, for example through the federal income tax, encouraging full participation in existing fiscal programs come at the price of considerably less labor supply, particularly among the poor. Thus, we have what might be considered a welfare paradox – more tax and benefit programs that claw back benefits in response to higher labor earnings, or greater participation in such programs, can induce less work, lower labor earnings, and, on balance, increase poverty.

Consider next figure 4, which retains our standard assumption of partial participation. The figure, whose dots are population weighted using our imputed state weights, shows that CMTRs are a very poor proxy for LMTRs for a large share of households. Were the two measures identical, all dots would lie along the chart's dashed 45 degree line. But for large numbers of households, particularly low-income households, the dots lie to the right of the 45-degree line. These are cases in which the LMTR exceeds the corresponding CMTR, often dramatically, due to double taxation.

There are also many cases, especially among those in the bottom quintile, in which things go the other way – the CMTR exceeds the LMTR, again, often dramatically. This is because the loss of benefits from welfare programs associated with extra income in the current year reduces savings. The reduction in savings may allow a household to pass asset tests and become eligible for the same, or other, welfare programs in subsequent years.

[38]Recall, these and all other statements incorporate SCF population weights adjusted by imputed state residency.

Figure 4: Current-Year vs Lifetime Marginal Tax Rates from $1,000 Earnings Increase in Current Year, Ages 20-69

Figures 3, A8, and 4, in conjunction, also convey a critical message. Contrary to the prescriptions of optimal tax theory, we find huge dispersion in values of both the LMTR and the CMTR among households at all ages with essentially the same level of lifetime resources. Absent some compelling rationale for this variation, this dispersion constitutes a potentially huge deadweight loss – one we partially assess in section 12.

For the poorest and 2nd quintiles, the LMTRs are extremely dispersed, as measured by their standard deviation. But for the other quintiles as well as the 5th and 1st percentiles, variation in LMTRs is generally much smaller. This is to be expected since, with some exceptions, most households eligible for income- and asset-tested benefit programs are in the first and second resource quintiles. Whereas most of our results focus on dispersion by resource and age, LMTRs also vary across other attributes. Table A7 summarize LMTRs by resource group and the number of under-18 children in the household. As shown, LMTRs in the bottom quintile are highest for those with only one or two children. This is because low-income households with only one or two children are, relative to those with 3+ children, more likely to fail demographic-dependent asset or income tests when receiving additional earnings. Those with no children likely qualify for fewer benefits and, consequently, face lower rates.

This effect is not, however, limited to the bottom quintile. Among middle-class households in the second, third, and fourth quintiles, each additional child significantly lowers the LMTR. For those in the third quintile, for example, the median LMTR is 44.5 percent for households with no children, but only 33.2 percent for those with three or more. For those in the fourth quintile, the corresponding rates are 48.1 percent and 41.9 percent.

7.4 Decomposing Average Marginal Net Tax Rates

Table 6 shows the sources of mean lifetime and current-year marginal tax rates for one particular group, the lowest resource quintile among 20-69 year-old SCF households. We present mean values to ensure that the elements in each column sum to totals. As shown, current-year taxes rise and current-year transfers fall with an increase of $1,000 in labor income, although one important transfer, the ACA subsidy, rises. The pattern is similar for the present value of lifetime net taxes, but the magnitudes are larger, especially for transfers.

Table 6: Breakdown of LMTR and CMTR sources, Lowest Resource Quintile

	C Baseline	C Marginal	C Diff	L Baseline	L Marginal	L Diff
Federal Income Tax	2,467	2,625	158	31,119	31,298	179
State Income Tax	436	458	22	5,089	5,117	28
Other Taxes	2,123	2,186	63	35,853	35,944	92
Total Taxes	5,025	5,269	244	72,060	72,360	300
SNAP	1,131	1,096	-34	8,952	8,885	-66
TANF	47	46	-1	85	84	-1
Section 8	225	224	-1	2,119	2,118	-2
CCDF	530	498	-31	2,083	2,051	-32
Social Security	736	736	0	75,473	75,491	17
SSI	270	256	-14	5,499	5,471	-28
Other Transfers	4,581	4,550	-31	92,757	92,735	-22
Total Transfer Payments	7,520	7,406	-113	186,968	186,834	-134
Net Taxes	**-2,494**	**-2,138**	**356**	**-114,908**	**-114,474**	**433**

Note: All numbers are calculated based on a $1,000 increase in current-year earnings. Weighted Mean values are presented.

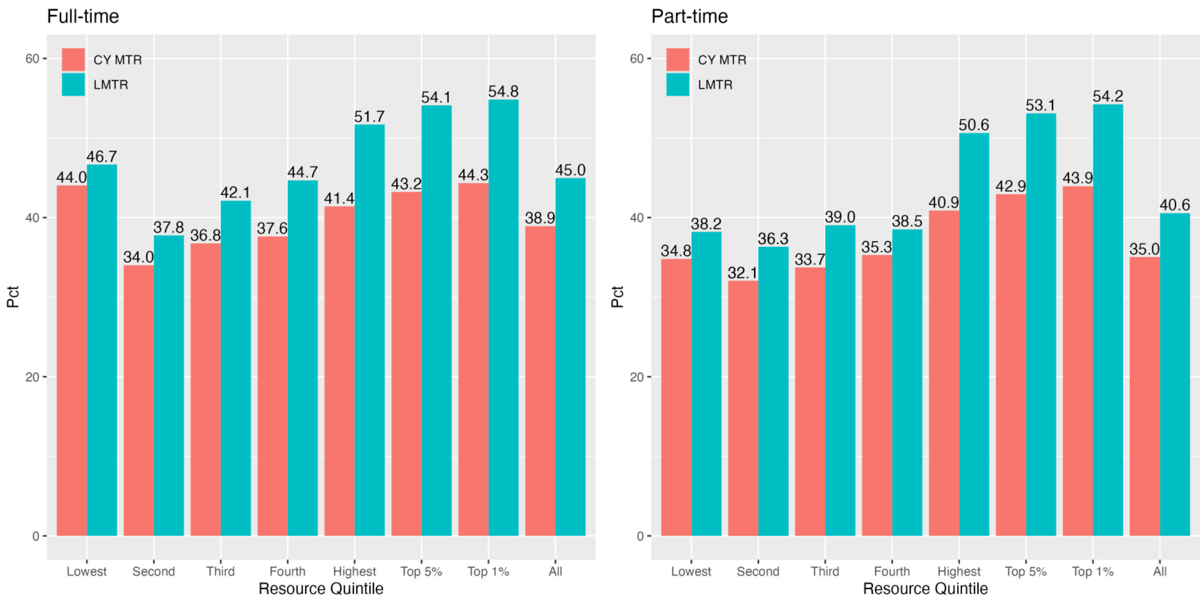
Table 6 shows that, for households in the bottom quintile, their 35.6 percent average CMTR arises from an average reduction of transfer payments of $113 and increase in taxes of $244 for $1,000 in additional current earnings. The corresponding present-value reduction in lifetime benefits is larger at $134. The increase in lifetime taxes is $300. $66 of the present-value reduction in benefits can be attributed to loss of SNAP benefits, and $32 to loss of CCDF.

8 The Cost of Labor Force Entry

This section considers the work-participation tax for the subset of SCF respondents who report they are neither working, disabled, collecting Social Security, nor older than their imputed retirement age. Rather than assume the households earn an extra $1,000, we assume they work either part-time, earning $15,000 annually, or full-time, earning $30,000 annually. We assume that the return to work is permanent – continuing through respondents' imputed retirement ages, with wages adjusting to inflation in future years. For a household with two respondents, we only consider a return to work by the household head. The two income levels simulate people going back to, respectively, approximately half-time and full-time work at an hourly wage rate of $15 per hour. We estimate CMTRs and LMTRs based on this amount.

Figure 5 summarizes. Across all households in our sub-sample, the median full-time work-participation LMTR is 45.0 percent. The median part-time work-participation LMTR is similar – 40.6 percent. For the bottom quintile, going back to full-time work entails both a higher median LMTR and CMTR with respective values of 46.7 percent and 44.0 percent. Part-time participation is taxed at a lower rate, although the median CMTR and LMTR are 34.8 percent and 38.2 percent, respectively.

Figure 5: Median LMTR and CMTR From Labor Force Entry, Pre-Retirement Age and Non-working SCF Households



Tables 7 and A8 decompose contributions to high rates from, respectively, returning to full-time and part-time work. For example, for an average working age, bottom-quintile non-working household, returning to full time at $15 an hour lowers their current-year SNAP benefits by $1,361 and the total amount of transfer payments received by over $5,000. The remainder of the average current-year tax bill of $12,137 comes from increased taxes. Even though their federal income tax rate is well under 20 percent, they still retain just slightly more than 50 cents for each dollar earned. The breakdown of lifetime taxes is similar, with an average lifetime work-participation tax increase of $125,789 based on average present value earnings of $291,785. Roughly $50,000 of this tax increase is from losses in benefits and $76,000 from higher taxes.

9 Cross-State Variation

This section describes the variation in lifetime marginal tax rates across U.S. states. In an earlier study, Fleck et al. (2021) characterize cross-state effective marginal tax rates, inclusive of transfers. Their focus is on state-by-state progressivity, which they derive from an estimated parametric tax function. Their estimation methodology differs from ours in that our approach is to calculate the actual distribution of marginal rates, and their approach differs from ours in other important aspects. For example, they do not adjust for data issues related to transfer program take-up in ASEC data, and they focus only on CMTRs. Nonetheless, they conclude that there is significant cross-state variation in marginal tax rates, as do we.

To illustrate how LMTRs vary by state, we calculate the median LMTR for households in the 30-39 age cohort in the lowest resource quintile in each state. (Recall that the quintiles are defined at the national level, so that moving from one state to another does not affect the quintile into which a household falls.) Figure 6 shows the cross-state variation in median lifetime marginal tax rates. Figure A11 in the Appendix provides similar information for the current-year marginal tax rates.

Table 7: Breakdown of LMTR and CMTR sources from Full-time Labor Force Entry, Pre-Retirement Age, Bottom Resource Quintile, Non-working SCF Households

	C Baseline	C Marg.	C Diff	L Baseline	L Marg.	L Diff
Federal Income Tax	1,669	6,589	4,920	15,324	68,797	53,473
State Income Tax	146	906	760	1,173	9,232	8,060
Other Taxes	347	1,721	1,374	15,141	29,792	14,651
Total Taxes	2,162	9,215	7,054	31,638	107,822	76,184
SNAP	1,793	432	-1,361	18,124	3,635	-14,489
TANF	182	2	-180	555	4	-550
Section 8	810	271	-539	11,294	5,033	-6,261
CCDF	359	206	-153	1,195	636	-559
Social Security	0	0	0	66,472	76,544	10,072
SSI	318	0	-317	10,185	2,302	-7,883
Medicaid	2,610	1,147	-1,463	31,287	14,418	-16,869
ACA	713	523	-190	9,057	7,432	-1,625
Other Transfers	1,309	430	-879	56,721	45,281	-11,439
Tot. Transfer Payments	8,094	3,011	-5,083	204,890	155,285	-49,605
Net Taxes	**-5,933**	**6,204**	**12,137**	**-173,252**	**-47,463**	**125,789**
Added Income	0	30,000	30,000	0	291,785	291,785

Note: All numbers are calculated based on a $1,000 increase in current-year earnings. Weighted Mean values are presented.

Figure 6: Cross-State Variation in Median LMTRs (Age 30-39, Lowest Resource Quintile)

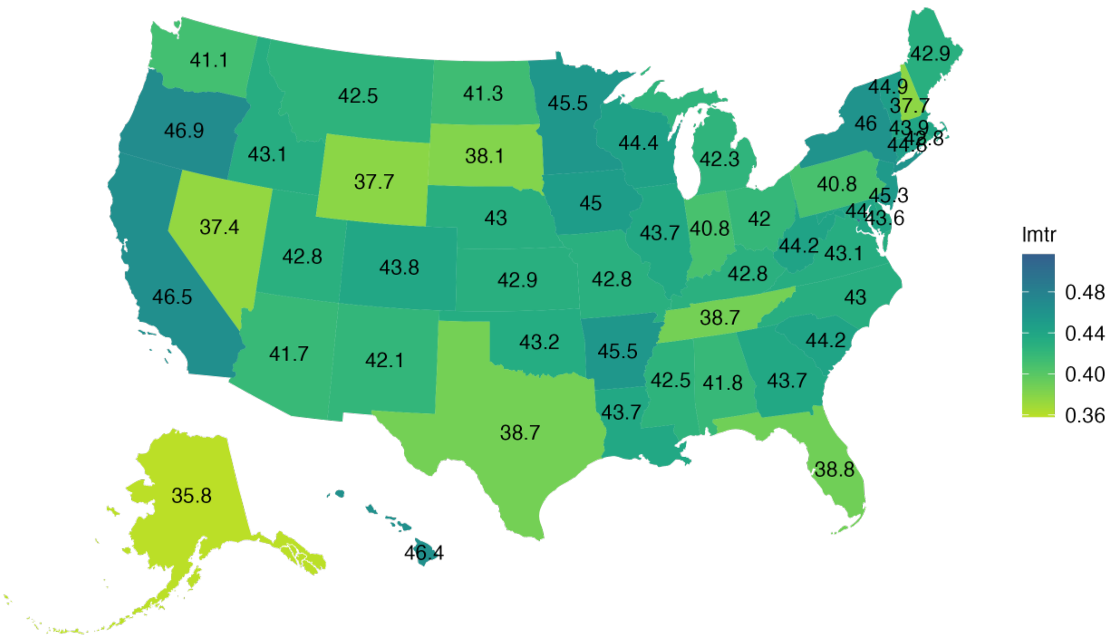


Figure 6 reveals significant state-level variation in *median* LMTRs for this subset of the population. The age-resource group's median rate varies between a low of 35.8 percent in Alaska and a high of 46.9 percent in Oregon. Clearly, where people live matters to their incentives to work. Another way to quantify the variation in lifetime marginal taxation across states is to calculate, for each household, the lifetime marginal tax rate it faces in each state and then compute the percentage point difference between the maximum and the minimum rates. Table 8 reports this measure for households for different resource quintiles.

Table 8: Measure of the State-Level LMTR Dispersion

	min	q25	median	mean	q75	q90	max	st.dev
Bottom	7.6	28.3	74.4	671.0	232.0	1,215.9	24,427.4	2,367.5
Second	6.5	12.0	21.6	95.6	84.6	171.0	4,157.2	243.5
Third	7.1	9.9	12.2	38.2	22.0	59.8	2,047.9	134.3
Fourth	5.7	9.8	10.6	19.1	14.6	27.6	771.8	33.9
Highest	6.0	10.1	11.4	25.4	18.9	41.2	3,219.5	95.4
Top 5%	6.5	10.3	11.8	38.2	15.5	34.3	3,219.5	128.5
Top 1%	8.0	11.2	12.5	18.6	13.3	26.3	781.4	61.5
All	5.7	10.1	12.7	95.5	29.9	93.0	24,427.4	652.4

Table 8 shows that state residency can matter enormously to the LMTR facing given households. This is particularly true for the bottom quintile, whose median max-min difference in marginal tax rates is an astounding 74.4 percentage points. A full quarter of those in this group can reduce their LMTR by over 230 percentage points by moving across states! The max-min differences are smaller for higher resource groups. But even among the top 1 percent, there's a 12.5 percentage point median max-min difference across states in lifetime marginal tax rates.[39]

10 Sensitivity to Amount of Added Income

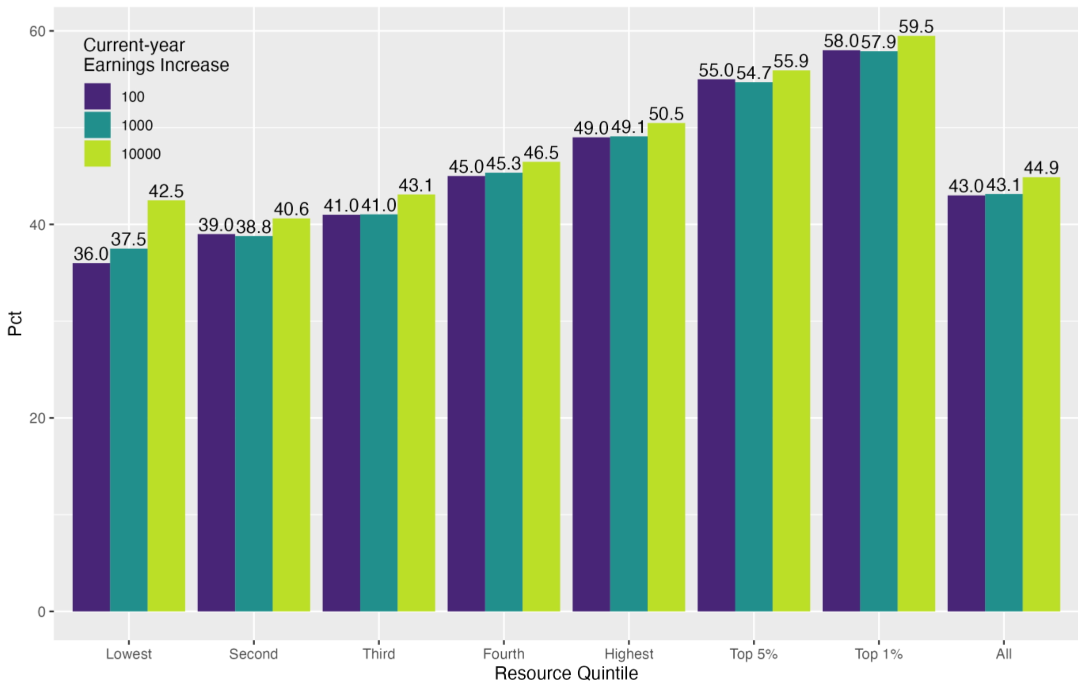
We next consider whether our LMTR and CMTR measures depend importantly on the size of the posited increase in earnings. To that end, we considered additional earnings of both $100 and $10,000. Figures 7 and A13 compare median LMTRs and CMTRs for the baseline (with $1,000 in additional earnings) and the two alternative experiments.

A quick glance indicates that our median findings are quite robust to the magnitude of the earnings increment. In the $1,000 baseline case, the overall median LMTR is 43.1 percent. It's 43.0 percent if we increase earnings by $100, and 44.9 percent if we increase earnings by $10,000. Corresponding CMTRs are 33.0 percent and 35.1 percent with a baseline of 33.3 percent.

The higher LMTRs when earnings increase by $10,000 reflects reflects two things. First, some additional low-resource households lose benefit-program eligibility with a larger earnings increase. Second, some high-resource households find themselves in higher federal tax brackets. For bottom quintile households, the LMTRs from increasing income by $100, 1,000, and $10,000 are 36.0, 37.5, and 42.5 percent respectively. For the top 1 percent, LMTRs are 58,0, 57.9, and 59.5 percent.

[39]Unsurprisingly, the major differences in state-specific marginal net taxation implies a major difference in average net taxation. Table A9 presents summary statistics for our measure of lifetime spending dispersion at the state level. The measure is constructed by calculating for each household the percentage increase from the lowest to the highest level of lifetime spending the household would experience were it to live in the respective states. As shown in table A9, the median 20-69 year-old SCF household could raise their lifetime living standard by 15.2 percent simply by moving from the state with the highest average net tax burden to that with the lowest.

Figure 7: Median LMTR by Amount of Added Income, Ages 20-69



11 Decomposing LMTRs by Fiscal Program

Here we consider the importance of specific individual fiscal policies or groups of policies to median LMTRs and CMTRs. Specifically, we show how the medians would change in the absence of a) the Earned Income Tax Credit (EITC), the Child Care Development Fund (CCDF), and the Child Tax Credit (CTC), denoted in figures 8 and 9 as no_{eitc}, b) SNAP and Section-8 housing, denoted as no_{fstmp}, c) Social Security, both the System's FICA tax and benefits, denoted no_{ss}, and d) state income taxes, denoted $no_{statetax}$.

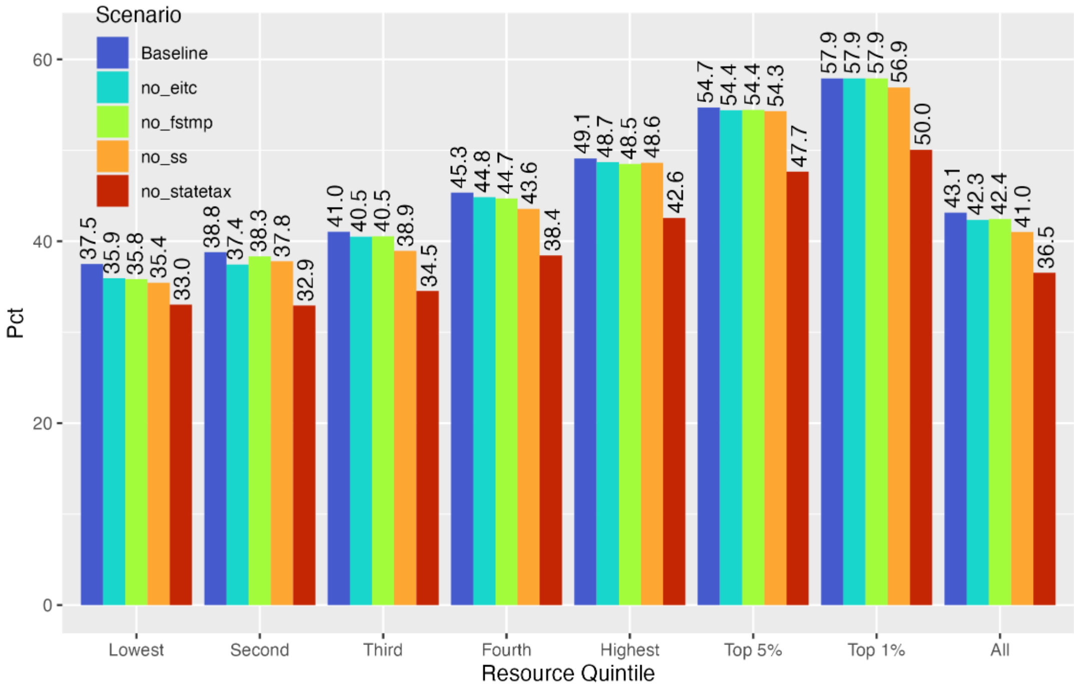
Interestingly, eliminating these combinations of programs or individual programs doesn't matter much to median values of LMTR – with one exception, state income taxes. For example, eliminating just the EITC, CCDF, and CTC reduces the overall median LMTR from 43.1 percent to 42.3 percent. Eliminating just SNAP food assistance and Section-8 housing reduces it to 42.4 percent. Eliminating Social Security cuts it to 41.0 percent. But eliminating state taxes has a bigger effect, reducing the median LMTR to 36.5 percent.

Part of the reason the combinations of benefit programs don't substantially alter the median LMTR is partial plan participation. A second reason is that these programs individually account for only a fraction of the LMTRs. But their impacts add up. Take the bottom quintile, for which the sum of impacts of separately eliminating the four sets of programs explains 9.9 percentage points of their 37.5 percent median LMTR. There are, of course, other fiscal policies that contribute significantly to both LMTR and CMTR even in the absence of the policies considered. These include the personal and corporate federal income taxes, state sales taxes, federal excise taxes, Medicare taxes, and the potential loss of SSI.[40]

In addition, eliminating particular programs can activate the work disincentives of others. For example, eliminating Social Security benefits means that many low-income elderly will qualify for SSI with its severe income and asset tests. When social security benefits are eliminated,

[40]The median LMTR for the bottom quintile in the absence of all tax and transfer programs except the personal federal income tax is 12.4 percent.

Figure 8: Median LMTR By Fiscal Program Elimination, Ages 20-69



households in the first resource quintile receive, on average, an additional \$12,873 in present-value SSI, Food Stamps, and Section 8 benefits. This difference reflects the increasing reliance on welfare programs in the absence of social security benefits. It also increases their LMTRs, all else equal, by placing more households in a position to lose benefits from additional income. Turning to median CMTRs, the most important stand-alone factor is turning off Social Security. Doing so reduces the overall median CMTR by 7.9 percentage points – to 25.4 percent. The reason is simple. The CMTR includes only current-year taxes and benefits: For working households, it includes the current FICA tax, but not future Social Security benefits.

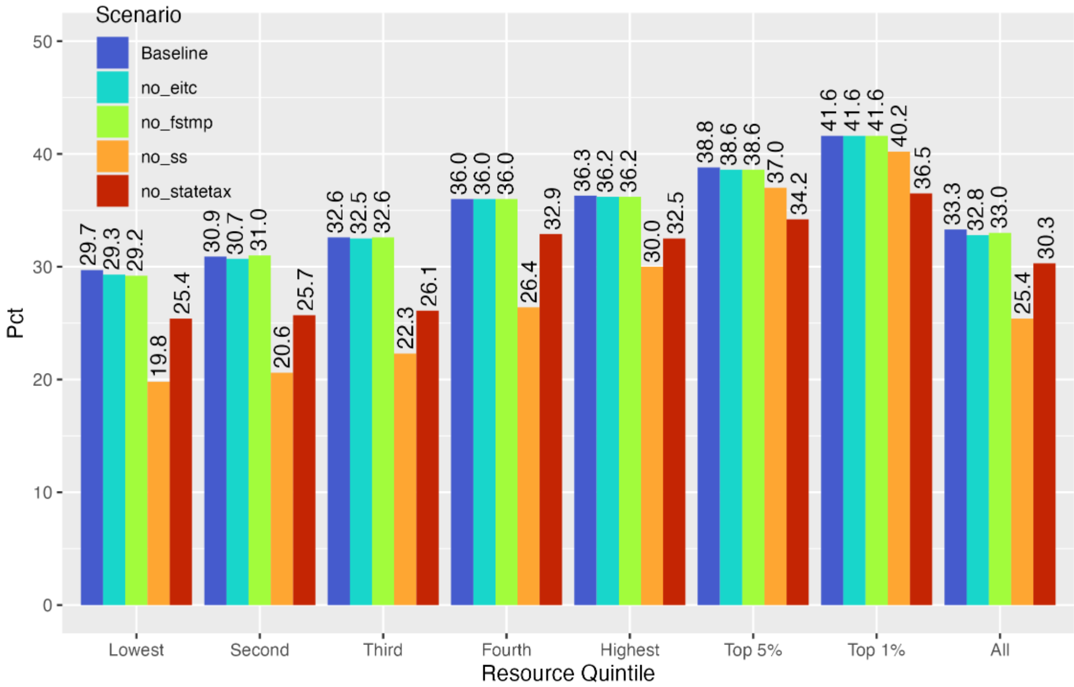
12 Excess Burden Arising from Marginal Tax Rate Dispersion

As stressed above, the current U.S. fiscal system imposes not only high LMTRs and CMTRs, but also considerable variation in rates among those of similar ages with similar levels of resources. Such dispersion can compound the distortions of high average marginal tax rates. Our final extension considers the deadweight loss (DWL) of this dispersion, contrasting the current fiscal system with one that would levy the same net tax on everyone with a given level of resources. Our focus is limited to the distortions arising with respect to current-year labor supply. We estimate DWL utilizing the following approximation. Let x be labor supply, t the marginal tax rate, and p the after-tax wage, defined as the gross wage multiplied by one minus the marginal tax rate. After-tax labor earnings is, thus, px. Consider the standard second-order approximation of DWL.

$$DWL \approx -\Big(t\Delta x + \frac{1}{2}\Delta t \Delta x\Big). \tag{15}$$

The first term in (15) is captured by $-t\Delta x \approx -t\frac{dx}{dp}(-\Delta t) = \frac{t}{p}\Big(\frac{dx}{dp}\frac{p}{x}\Big)x\Delta t$, where $\Big(\frac{dx}{dp}\frac{p}{x}\Big)$ is

Figure 9: Median CMTR By Fiscal Program Elimination, Ages 20-69



the price elasticity of x. Assuming that all households in a particular age-resource cohort have the same price elasticity, the sum of this expression over households in a given cohort i is

$$\left(\frac{dx}{dp}\frac{p}{x}\right)\sum_i \frac{t_i}{p_i} x_i \Delta t_i. \tag{16}$$

Further, suppose that variations in tax rates are revenue compensating such that the static revenue is unchanged. Then, $\sum_i x_i \Delta t_i = 0$. In general, the first-order term in (16) is non-zero unless the tax rate terms $\frac{t_i}{p_i}$ are uncorrelated with the terms $x_i \Delta t_i$. However, if we group households within a cohort such that they have the same initial tax rate and the wage rate, expression (16) becomes

$$\frac{t}{p}\left(\frac{dx}{dp}\frac{p}{x}\right)\sum_i x_i \Delta t_i \tag{16*}$$

which equals 0 by the assumption that the static revenue remains unchanged. Then, equation (15) simplifies to $-\frac{1}{2}\sum_i \Delta t_i \Delta x_i$, which we approximate by

$$\begin{aligned} -\frac{1}{2}\sum_i \Delta t_i \frac{dx}{dp}(-\Delta t_i) &= \frac{1}{2}\sum_i \left(\frac{dx}{dp}\frac{p}{x}\right) p_i x_i \left(\frac{\Delta t_i}{p_i}\right)^2 \\ &= \frac{1}{2}\left(\frac{dx}{dp}\frac{p}{x}\right)\sum_i p_i x_i \left(\frac{\Delta t_i}{p}\right)^2. \end{aligned} \tag{17}$$

Expressing DWL as a faction of cohort net income, $D = \sum_i p_i x_i$, (17) becomes

$$\frac{1}{2}\left(\frac{dx}{dp}\frac{p}{x}\right)\sum_i \frac{p_i x_i}{D}\left(\frac{\Delta t_i}{p}\right)^2. \tag{17*}$$

Additionally, recall that we assume $\sum_i x_i \Delta t_i = 0 \rightarrow \sum_i \frac{p_i x_i}{D} \frac{\Delta t_i}{p_i} = 0$. Hence, (17) can be rewritten as:

$$\frac{1}{2}\Big(\frac{dx}{dp}\frac{p}{x}\Big)\sum_i \left(\frac{p_i x_i}{D}\Big(\frac{\Delta t_i}{p}\Big)^2 - \Big(\sum_i \frac{p_i x_i}{D}\frac{\Delta t_i}{p_i}\Big)^2\right). \tag{18}$$

In principle, $p_i x_i$ is the after-tax income for household i in the initial equilibrium with no tax rate variation within their cohort. This is not observed, nor can it be imputed without significant error.[41] Therefore, we treat all households in the labor force (i.e. all who are included in the calculation, excluding those where all main respondents are fully retired or disabled) within each cell as having not only the same value of the after-tax wage, p_i, but also the same initial after-tax labor income $\overline{px}$. Under this assumption, $\frac{p_i x_i}{D} = \frac{1}{N}$, where N is the population-weighted number of households in this cell. This allows us to further simplify (18) to

$$\frac{1}{2}\Big(\frac{dx}{dp}\frac{p}{x}\Big)\frac{1}{N}\sum_i \left(\Big(\frac{\Delta t_i}{p}\Big)^2 - \Big(\sum_i \frac{\Delta t_i}{p}\Big)^2\right) = \frac{1}{2}\Big(\frac{dx}{dp}\frac{p}{x}\Big) wvar\Big(\frac{\Delta t_i}{p}\Big), \tag{18*}$$

where the variance accounts for either our imputed household weights or each household's weighted observed labor income share of the cohort.[42] The former would bias our calculation upward as it assigns equal contribution to DWL of those with lower income. The latter would bias downward, to the extent that those with high marginal tax rates actually work less than those with lower marginal tax rates.

To calculate $\overline{px}$ for a particular age-resource cohort, we utilize the fact that the observed after-tax wage for household i is $p_i = w_i(1-\theta_i)$, where w_i is the pre-tax wage and θ_i is the household's LMTR. [43] The household's labor income is, consequently, $w_i(1-\theta_i)x_i$. The average MTR for the cohort $\bar{\theta}$ equals the average of θ_i weighted by observed before-tax income $w_i x_i$. The cohort's average after-tax income $\overline{px}$ equals $1-\bar{\theta}$ multiplied by average before-tax income. Using the same notation, $\Delta t_i = w_i(\theta_i - \bar{\theta})$. Therefore,

$$\frac{\Delta t_i}{p} = \frac{\theta_i - \bar{\theta}}{1-\bar{\theta}} \tag{19}$$

We estimate DWL for two scenarios, assuming, respectively, realistic and full welfare-program participation.[44] Results are presented in tables 9 and 10. For each table, we present results based on income weights and population weights. As discussed, these two weights should provide lower and upper bounds for DWL, given an assumed degree of behavioral response. We also consider three possible degrees of behavioral response, as represented by the Frisch elasticity of labor

[41] For example, individuals who are driven not to work by their actual marginal tax rates might work at a lower marginal tax rate, but might still choose not to work. Also, it is hard to interpret the positive labor supply observed for individuals for whom we calculate marginal tax rates above 100 percent.

[42] Note that income weights should account for the cohort's income share represented by a given household. In other words, each household's weight is its labor income multiplied by the household population weight.

[43] We use the LMTR to estimate deadweight loss, rather than the CMTR, consistent with our reasoning that it is the LMTR that should influence labor supply decisions.

[44] As we assume a constant elasticity of labor supply, we remove outliers to prevent results from being dominated by individual households with extraordinary marginal rates. Specifically, we remove households with the bottom and top 1% of LMTRs from each resource group, any household where the main respondent is disabled or retired, and households with exactly 0 current-year total labor income across all respondents. We also remove cases with an LMTR greater than 500%.

supply. Following the review by Reichling and Whalen (2012), we consider low, mid-range, and high values of the Frisch elasticity of 0.27, 0.4, and 0.53.

Table 9: Percent Deadweight Loss By Resource Group, Imputed Welfare Participation

	Population Weighting			Income Weighting		
Res. Group	Low	Mid	High	Low	Mid	High
Bottom	12.3	18.2	24.1	8.9	13.2	17.5
Second	1.2	1.8	2.4	0.9	1.3	1.7
Third	0.3	0.4	0.5	0.3	0.4	0.5
Fourth	0.3	0.4	0.6	0.3	0.4	0.6
Highest	0.6	0.8	1.1	0.6	0.8	1.1
All	1.3	1.9	2.5	0.7	1.0	1.4

Table 10: Pct. Deadweight Loss By Resource Group, Full Welfare Participation

	Population Weighting			Income Weighting		
Res. Group	Low	Mid	High	Low	Mid	High
Bottom	51.9	76.9	101.9	34.5	51.1	67.7
Second	8.4	12.4	16.4	8.2	12.1	16.0
Third	0.4	0.6	0.8	0.4	0.5	0.7
Fourth	0.3	0.5	0.6	0.3	0.4	0.6
Highest	0.5	0.7	1.0	0.5	0.8	1.0
All	3.7	5.4	7.2	1.3	2.0	2.6

Table 9 shows that the deadweight loss caused by dispersion of marginal tax rates on current labor income are, in the aggregate, nontrivial. At the midpoint value for the Frisch elasticity, the overall deadweight loss lies between 1.0 and 1.9 percent of labor income. However, this overall result masks sharp differences by income. Consistent with the much higher variation in marginal tax rates at the bottom of the resource distribution, the deadweight loss for those in the lowest quintile ranges from 8.9 percent to 24.1 percent of labor income.

This range would be substantially higher if there were full take-up of benefits, as shown in table 10. Even if we assume a low estimate for the Frisch elasticity, the DWL for those in the bottom quintile ranges between 34.5 and 51.9 percent. For the second quintile, it is roughly 8 and 12 percent assuming, respectively, low and midpoint elasticity. In summary, in addition to the deadweight loss normally associated with the distortion of labor supply by the tax and transfer system, there is considerable additional loss coming from the dispersion of marginal tax rates, even when one takes account of the partial take-up of government-provided benefits.

13 Conclusion

A fundamental aspect of every nation's fiscal policy is the degree to which it encourages or discourages labor supply. This paper provides the most comprehensive-to-date analysis of this fundamental aspect of U.S. fiscal policy. It does so by computing marginal lifetime net tax rates (LMTRs) – the additional present value of taxes less the additional present expected value of benefits associated with additional earnings. Expected references considering each of a household's future survivor paths. Our analysis focuses strictly on measuring the fiscal system's net work disincentives, not reactions to those disincentives. We control for preferences by assuming exogenous labor earnings and consumption smoothing.

Our study incorporates all major federal and state fiscal policies, benefit-program take up, and forming lifetime, not just current-year measures. A lifetime focus is critical. Our fiscal system is intertemporally intertwined. Social Security is a prime example. Paying more FICA taxes now generally means more benefits in the future. In some cases, the system's extra benefits can exceed, on an expected present value basis, its extra taxes. Hence, current-year marginal net taxes (CMTRs), which ignore future benefits, can't accurately capture current-year work disincentives.

Our study applies the Fiscal Analyzer (TFA) – a life-cycle consumption smoothing tool – to the 2019 Survey of Consumer Finances to study the marginal net taxation of Americans' labor supply. We calculate how much each household is able to spend on an expected (average) present-value basis, where averages are formed over the household's spending (discretionary plus non-discretionary, including housing costs and in-kind Medicare and Medicaid healthcare transfers) over each of its potential survival paths. We then compare this remaining expected lifetime spending with the corresponding amount the household can expect to spend were it to earn more either on a temporary (current year) basis. Dividing the difference in present value spending by the present value change in human wealth delivers the household's remaining lifetime marginal net tax rate (LMTR). Given lifetime budget balance along each survivor path, the LMTR also equals the expected present value increase of a household's net taxes divided by the posited increment to the present value of labor earnings.

Our findings are striking. Even accounting for partial benefit-program take up, American households typically face very high LMTRs. Among all households headed by respondents age 20-69, the median LMTR is 43.1 percent. For the bottom lifetime-resource quintile, the median rate is 37.5 percent. For the top quintile, it's 49.1 percent. And for the top 1 percent, it's 57.9 percent. LMTRs steadily rise with household resources. However, were all Americans to participate in all benefit programs for which they are eligible, the marginal tax-rate versus resources pattern would, instead, be U-shaped. Another key finding is the major importance of double net taxation. The median LMTR across our entire sample of 43.1 percent is close to one-third higher than the corresponding current-year marginal net tax rate of 33.3 percent.

We find tremendous dispersion in work disincentives across households with essentially identical levels of remaining lifetime resources. The greatest dispersion arises among bottom-quintile households. Consider the poorest fifth of those 30-39 years-old. Their 25th, 50th, and 75th lifetime marginal net tax rate percentile values are 27.2 percent, 41.5 percent, and 51.9 percent. For this age cohort, the standard deviation in LMTRs is almost fifty times larger for the bottom than for the top quintile.

Work disincentives are extraordinarily high for a significant fraction of low-wage workers. One in ten face lifetime marginal tax rates rates above 70 percent, effectively locking them out of the labor force and into poverty. This poverty lock would be far worse were all the poor to participate in all benefit programs for which they are eligible. For those not working, the marginal tax on working part-time or full-time for the rest of one's life are also very high, reaching close to 50 percent for those in the bottom quintile contemplating full-time work. Much of the dispersion in work disincentives arises due to variation across states in benefit-program provisions. Indeed, we find that the typical SCF household can dramatically alter their marginal net tax rate and lifetime spending simply by moving states. Our simplified excess burden calculation produces an efficiency loss ranging as high as nearly one quarter of labor earnings for bottom-quintile workers.

In sum, an analysis of the U.S. fiscal system that fully accounts for all major federal and state fiscal policies reveals major work disincentives, a significant poverty lock, huge horizontal differences in work disincentives potentially producing major efficiency costs, extreme differences across state lines in such disincentives, the importance of considering a lifetime rather than a current-year perspective, and, most important, the need for policy coordination that rationalizes an extremely balkanized fiscal system.

Finally, our results raise an issue considered in the literature reviewed extensively in Kaplow (2024), that workers may confuse marginal and average tax rates. This confusion may extend to focusing on gross rather than net marginal rates and to current-year rather than lifetime marginal net taxation. What tax rates are salient to actual labor-supply decisions is a subject for ours and others' future work. But one surely needs comprehensive, accurate measures of lifetime, current-year average and marginal gross and net tax rates to improve such behavioral analyses. Moreover, as indicated in Brumm et al. (2024), economics may rapidly be reaching a point where it can elicit a household's preferences and suggest optimal behavior. Advances like this could themselves promote more informed decisions on the part of households.

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Appendix

A1 Additional Benchmarking, Imputation, and Adjustment Details

A1.1 Benchmarking the 2019 SCF to National Aggregates

We follow the approach outlined in Appendix A and B in Dettling et al. (2015) to benchmark the 2019 SCF to national aggregates. Specifically, we set SCF benchmark factors to ensure that SCF-weighted aggregates coincide with conceptually equivalent NIPA and FA aggregates. We used FA2018 Q4 aggregates for wages, self-employment income, and assets.

Benchmarking assets and net worth reported in the SCF requires several adjustments to the Financial Accounts values. Using the approach outlined in Dettling et al. (2015), our first asset adjustment is to reduce SCF-reported home market value by 7.3 percent to match the 2018 Q4 Federal Reserve Financial Accounts measure. Second, we increase the SCF-reported equity in non-corporate businesses by 33.3 percent to match the 2019 Q3 Federal Reserve Financial Accounts estimate. Third, we increase reported retirement account assets by 11.3 percent to match the total reported for 2018 Q4 in the Federal Reserve's Financial Accounts.

Table A1 details aggregate values, their sources, and our benchmark adjustments. We inflate all SCF-reported wage income by 22.3 percent to match the NIPA 2018 measure of employee compensation, and deflate all SCF-reported self-employment income by 28.4 percent to match the NIPA 2018 proprietorship and partnership income total.[45]

Table A1: SCF Benchmarking Adjustments and Targets

	SCF Unadjusted	Benchmarking Coefficient	SCF Adjusted	Target	% Diff
Wages	7,382[46]	1.22	9,027	9,027	0.0
Self Employment Income	2,237	0.72	1,601	1,601	0.0
Market Val. of Homes	28,048	0.93	25,992	25,877	0.4
Non Corp. Business Equity	9,795	1.33	13,055	13,055	0.0
Regular Assets	50,904	0.69	35,373	35,374	0.0
Retirement Accounts	14,307	1.11	15,923	15,824	0.6

A1.2 Imputing State Residency

The public-use SCF does not provide state identifiers. The non public-use SCF data does include state identifiers, but its household weights are national, i.e., not state-specific. They are, therefore, of no value for our purposes of appropriately allocating SCF households by state. Consequently, we impute state residency based on a statistical match to the 2019 American Community Survey (ACS). Having done so, we calculate the distribution across states of ACS

[45] The fact that we need to inflate wage income and significantly deflate self-employment income to match national aggregates may reflect, in part, a tendency of SCF respondents to report wage earnings as self-employment income. There is also evidence that noncorporate business income is overstated for other reasons, including the underreporting of business losses. See Bhandari et al. (2020).

[46] All values are presented in billions of 2018 U.S. dollars.

households with specific cell characteristics. Next, we assign each SCF household to each of the 51 states in appropriate proportion such that the sum of each household's state-specific weights equals its original SCF weight.

Specifically, we partition households into distinct cells based on the household head's age, race/ethnicity, marital status, educational attainment, as well as home ownership status, total household income in 2018, and the number of children in the household under 17 years of age.[47] For households in a given cell, we create the household's weight for each state by multiplying their SCF sample weight by the weighted fraction of the cell's households in the 2019 ACS that reside in that state. Thus, the sum of all state weights for each state will equal the population of that state. We then run TFA 51 times, once for each state plus D.C., incorporating, in the process, each state's specific tax and transfer policies.

Note that the categorization of rich and poor by resources is done at the national level. So, for example, California has a higher weighted fraction of its households (17.1 percent) in the top 10 percent of lifetime resources than does Mississippi (4.5 percent), and has significantly more residents. Thus, resource-rich households in the U.S. are much more likely to be located in California than in Mississippi (18.2 percent of the top 10 percentile of households are in California versus 0.4 percent in Mississippi).

A1.3 Earnings Imputations

To impute past and future annual labor earnings, we first group CPS observations by age, sex, and education. Next, we estimate annual earnings growth rates by age and year for individuals in each sex and education cell. These cell growth rates are used to backcast and forecast each individual's earnings history.[48] Past and future cell growth rates ignore earnings heterogeneity within cells. To deal with such heterogeneity, we assume that observed individual deviations in earnings from cell means are partially permanent and partially transitory, based on an underlying earnings process in which the permanent component (relative to group-trend growth) evolves as a random walk and the transitory component is serially uncorrelated. We also assume that such within-cell heterogeneity begins in the first year of labor force participation.

In particular, suppose that, at each age, for group i, earnings for each individual j evolve (relative to the change in the average for the group) according to a shock that includes a permanent component, p, and an i.i.d. temporary component, e. Then, at age a (normalized so that age 0 is the first year of labor force participation), the within-group variance will be $\alpha\sigma_p^2 + \sigma_e^2$. Hence, our estimate of the fraction of the observed deviation of individual earnings from group earnings, $(y_{i,j}^a - \bar{y}_i^a\ )$, that is permanent is $a\sigma_p^2/(a\sigma_p^2 + \sigma_e^2\ )$. This share grows with age, as permanent shocks accumulate. Using this estimate, we form the permanent component of current earnings for individual j, $\hat{y}_{i,j}^a$,

$$\hat{y}_{i,j}^a = \bar{y}_i^a + (a\sigma_p^2/(a\sigma_p^2 + \sigma_e^2))(y_{i,j}^a - \bar{y}_i^a) = (a\sigma_p^2/(a\sigma_p^2 + \sigma_e^2))y_{i,j}^a + (\sigma_e^2/(a\sigma_p^2 + \sigma_e^2))\bar{y}_i^a \qquad (20)$$

and assume that future earnings grow at the group average growth rate. Further, we make the simplifying assumption that the permanent and temporary earnings shocks have the same variance, a reasonable one based on the literature (Meghir and Pistaferri 2011; Moffitt and

[47] We generate age groups in 10-year intervals. The 10-19 age group is combined with the 20-29 group, and the 90-99 group with the 80-89 group. We bin race/ethnicity groups to white or non-white, and education to three bins: high school diploma or less, some college, college diploma. Income groups are designated using total income quintiles. The number of under-17 children is top coded at 3.

[48] These forecasts assume zero real growth rate in economy-wide earnings.

Gottschalk 1995). Then, (11) reduces to:

$$\hat{y}^a_{i,j} = (a/(a+1))y^a_{i,j} + (1/(a+1))\bar{y}^a_i \tag{21}$$

For backcasting, we assume that earnings for individual j were at the group mean at age 0 (i.e., the year of labor force entry), and diverged smoothly from this group mean over time, so that the individual's estimated earnings t years prior to the current age a are

$$\bar{y}^{(a-t)}_i + ((a-t)/a)(\hat{y}^a_{i,j} - \bar{y}^a_i)(\bar{y}^{(a-t)}_i/\bar{y}^a_i) = (t/a)\bar{y}^{(a-t)}_i + ((a-t)/a)\hat{y}^a_{i,j}(\bar{y}^{(a-t)}_i/\bar{y}^a_i) \tag{22}$$

That is, for each age we use a weighted average of the estimate of current permanent earnings, deflated by general wage growth for group i, and the estimated age-a, group-i mean also deflated by general wage growth for group i, with the weights converging linearly so that as we go back we weight the group mean more and more heavily, with a weight of 1 at the initial age, which we assume is age 20.

A1.4 Using the American Community Survey to Impute Retirement Probabilities

As discussed in Altig et al. (2022), SCF respondents are asked about their expected ages of retirement. Not all respond and those that do may be overly optimistic about how long they will continue to work.[49] This squares with the tendency of workers in general to overestimate how long they will work (Center for a Secure Retirement 2019). As an alternative, we use the 2000 through 2020 waves of the ACS to impute retirement age based on two questions in the survey. The ACS asks respondents the number of weeks that they worked last year and the number of hours they are currently working in a typical week. We define a person as having "retired" when that person worked more than 26 weeks in the previous year and works less than 21 hours a week this year.[50] We segregate ACS working respondents by year of birth, age, gender, marital status, and education, assuming no retirement prior to age 50. This lets us calculate, for each cohort and combination of cell attributes, sample retirement probabilities over the twenty ACS surveys.

We smooth these values and use the resultant smoothed function to determine retirement probabilities. For cohorts retiring after 2020, we linearly project retirement hazards at each age based on 2000-2020 trends through 2040, and assume constant hazards thereafter. These cohort- and characteristics-specific retirement hazards are used to randomly assign retirement ages for each SCF respondent under age 80. We assume that all households retire at 80 if they haven't yet been probabilistically retired.[51]

The predicted age-specific fraction of ACS respondents working after 55 increases over time. The drivers here include higher educational achievement among successive cohorts and a rise in the fraction of working women. Consequently, within each cohort we project some, but rather limited, increases in retirement ages through 2040, with married 50 year-old men with

[49] Among 45 to 62 year-old 2019 SCF male respondents, the average age of expected full retirement is 70.3 years old, calculated using sample weights. For females, the weighted self-reported full retirement age is 68.9 years old. In 2018, the Social Security administration (2019) reported an average retirement benefit claiming age of 64.8 among men and 64.7 among women.

[50] We include 20 hours as retired because many ACS respondents report exactly 20 hours. These respondents are likely earning less than the SS Earnings Test threshold and hence are likely taking SS retirement benefits.

[51] Summaries of average retirement ages and conditional probabilities of working at age 65 and 70 for 50 year-old workers in 2020 are summarized in tables A2 and A3.

four-year college degrees or more retiring at 65.9, approximately 0.6 years later than their 2020 counterparts.

Figure A1 plots our cohort-specific smoothed retirement hazard functions – the likelihood of working "full time" (more than half time) at different ages – for alternative birth cohorts. Two things are immediately clear. First, regardless of year of birth, the probability of working "full time" declines dramatically starting at age 50. Second, recent cohorts are more likely to work after age 60, but the differences are small and decrease with age.

Figure A1: Fraction of Respondents Working More than 20 Hours Per Week, ACS 2000-2020

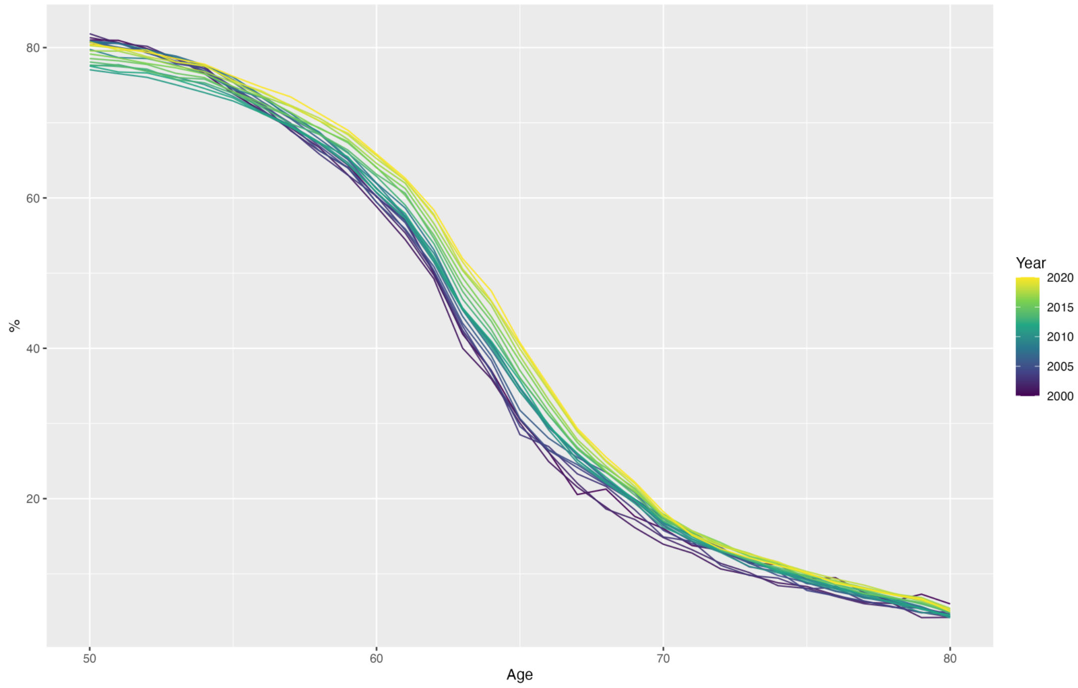


Table A2 shows projected average retirement ages for workers age 50 in 2020 and 2040, respectively. Results are broken down by marital status and education. First, predicted average retirement ages are only slightly higher for future than for current age-50 workers. Second, single females with college educations are projected to "retire" roughly two years later, on average, than those with a high-school diploma or less. Third, for males, education makes little difference in average "retirement" ages holding fixed marital status. Fourth, married males "retire," on average, roughly two years later than single males across all levels of education. Fifth, males "retire" later than females with the difference in average ages falling from roughly four years to roughly two years as one moves from lower to higher levels of education.

Table A2: Projected Average Retirement Age

		Age 50 Workers in 2020		Age 50 Workers in 2040	
Marital Stat.	Education	Male	Female	Male	Female
Single	High School or Less	63.0	59.4	63.1	59.0
	Some College	62.9	61.0	62.7	60.8
	4 yr. College or More	63.2	61.5	63.3	61.7
Married	High School or Less	64.9	58.1	65.4	58.4
	Some College	64.9	58.5	65.1	58.9
	4 yr. College or More	65.3	58.3	65.9	58.5

Table A3 reports the probability of working "full time" at ages 65 and 70 for 50 year-old workers in 2020. The table is quite revealing. First, holding education and marital status fixed, the chances of working "full time" are substantially higher at age 65 than at age 70. Take, for example, married males with some college education. Their chances of being "fully employed" are 56.0 percent at age 65 and 25.1 percent at age 70. Second, females are substantially less likely than males to work "full time." Third, married males are more likely to keep working "full time" than single males. And fourth, education significantly raises the likelihood of single, but not of married females working "full time."

Table A3: Probability of Working More than 20 Hours, Age 50 Workers in 2020

		Prob. of working more than 20 hours at age 65		Prob. of working more than 20 hours at age 70	
Martial Stat.	Education	Male	Female	Male	Female
Single	High School or Less	44.2	24.5	20.0	6.9
	Some College	43.2	34.0	17.3	11.0
	4 yr. College or More	45.3	35.9	18.4	10.5
Married	High School or Less	56.5	17.9	26.6	3.9
	Some College	56.0	20.3	25.1	4.7
	4 yr. College or More	58.6	18.9	26.5	3.9

A1.5 Adjusting for Benefit-Program Take-Up

As is well known, not all households file for all, or indeed any, welfare benefits for which they are eligible (Chien 2015; Giannarelli 2019). We make a variety of adjustments, imputations, and assumptions to assign take-up of each benefit to our SCF respondents. As we show, failure to address take-up can dramatically overstate marginal net tax rates, particularly among those with low incomes.

The adjustments include benchmarking each program's take-up rate to accord with the program's national take-up rate as reported by relevant government agencies. These are summarized in table A4. Our analysis relies, in part, on benefit-participation data reported in the the Annual Social and Economic Supplement (ASEC) to the Current Population Survey. The ASEC includes participation data on the following programs whose participation is not fully recorded by the SCF: SNAP, Section 8 Housing, the Affordable Care Act, the EITC, Adult and Child Medicaid, and the Child Tax Credit.[52]

As for the SCF, it records household Medicaid participation, although it does not report whether participants are children, adults, or both. The SCF also indicates if the household is receiving benefits from one or more of TANF, Food Stamps, SSI, or other programs. However, it does not report the exact program, and the total amount is often unreported.

The ASEC is also problematic for inferring take-up. It generally under-reports participation rates relative to official figures. For example, in the ASEC 40.0 percent of eligible households participate in SNAP while the official take-up rate is 67.6 percent. Hence, using the ASEC to predict SNAP take-up among SCF respondents requires first benchmarking SNAP participation in the ASEC to the official figure.

We do so by assigning participation to a set of ASEC respondents who did not report participating in SNAP. The set of reassigned respondents was determined based on a logit regression

[52]The referenced calculation of the Child Tax Credit take-up rate may be biased based on reasons discussed in Meyer et al. (2020), Jones and O'Hara (2016), and Imboden et al. (2023).

relating reported SNAP participation in the ASEC against respondent characteristics. The reassigned respondents are those non-SNAP participants with highest predicted SNAP participation probabilities. Thus, if we need X more ASEC respondents to participate in SNAP to equate the ASEC SNAP participation rate with the national rate, we reassign the top X ASEC non-participants, where "top" references participation probability ranking.

Next we estimate a second ASEC logit model using covariates that are common to the ASEC and SCF, specifically marital status, household size, income, education, and the amount they would receive if participating. Then, we assign SNAP program participation to SCF households based on their regression-based ranking of predicted program participation.[53] The cutoff for SCF SNAP participation is set to achieve the national rate. We follow this procedure for benchmarking each of the other benefits whose participation is solicited in the ASEC.

Table A4: Estimated Participation and Take Up of Public Assistance Programs

	Number of Participating Individuals ('000)	Number of Eligible Individuals ('000)	Take Up Rate (%)
SNAP	40,776	60,334	67.6
Housing Choice Voucher	5,249	46,559	11.3
Medicaid for Adults*	18,040	24,096	79.9
Medicaid for Children/CHIP**	35,953	38,370	93.7
ACA Subsidy	9,593	112,942	8.5
EITC	N/A	N/A	78.1
CTC	48,962	58,081	84.3
TANF	1,213	4,869	24.9
CCDF Childcare Subsidy	2,099	8,417	24.9

* Excluding dual Medicaid-Medicare enrollees and non-elderly adults with disabilities
** Excluding children with special needs care
Sources: Number of eligible individuals for each program are computed using the Policy Rules Database (Ilin and Terry 2021) applied to the 2019 Annual Social and Economic Supplement of the Current Population Survey. SNAP enrollment numbers are from SNAP Data Tables, Food and Nutrition Service, U.S. Department of Agriculture. Section 8 Housing Voucher enrollment data is from 2019 Picture of Subsidized Households, United States Department of Housing and Urban Development. Enrollment in Medicaid and CHIP is from Open Data, Center for Medicare and Medicaid Services; ACA Premium Subsidy enrollment is from 2019 Marketplace Open Enrollment Period Public Use Files, Center for Medicare and Medicaid Services. Estimates of the EITC take up is taken directly from the Internal Revenue Services. Number of tax returns with CTC is from Estimates of Federal Tax Expenditures for Fiscal Year 2019-2023, Joint Committee on Taxation. Data on the number of participating and eligible units for TANF is taken from Giannarelli (2019). Data on the number of participating and eligible units for CCDF is taken from Chien (2019).

We also impute take-up in the SCF for several programs not included in ASEC. In the case of SSI and Energy Assistance, we assume full take-up by eligible SCF households. As for CCDF, we randomly assign participation to eligible SCF households. For the remaining programs, we take the following approach. We know if a household is receiving benefits from either SNAP, TANF or SSI, but we do not have information on the specific program(s) from which the benefits are received. If an SCF household (1) reports receiving benefits from any of the three programs, (2) is not eligible for SSI, and (3) is eligible for SNAP, we assume that they are receiving SNAP benefits only, as very few households receive TANF. This produces close to 30 percent participation. We impute the remainder using the logit regression approach outlined above.

Child Medicaid has a very high participation rate – 93.7 percent. If an SCF household reports receiving Medicaid, is eligible for Child Medicaid, and has children younger than 18, we assume

[53]For SNAP and other programs, we randomly assign participation status using the same respective takeup rates as those who are eligible. This process is needed because some households may become eligible later in life, or through the additional income we assign to estimate marginal tax rates.

that they participate in Child Medicaid. If they report receiving Medicaid, are childless, and are eligible for Adult Medicaid, we assume that they participate in Adult Medicaid. As for adults otherwise unassigned to Adult Medicaid, but who are eligible, we use our logit-based assignment method. Finally, we randomly assign TANF to those who are eligible to reach our benchmark for the program.

Table A5 summarizes the results of our imputation for the programs for which we have aggregate participation rates. As shown, the procedure matches weighted participation rates for SCF respondents to within 0.2 percentage points of estimated national take-up rates.

Table A5: Summary Statistics for Welfare Program Participation Imputation

	Total Eligible	Total Assigned	Unweighted Participation Rate (%)	Weighted Participation Rate (%)	Takeup Rate Target	Diff
SNAP	905	631	69.7	67.7	67.6	0.1
Section 8	646	72	11.1	11.3	11.3	0.0
Medicaid Adult	706	579	82.0	80.1	79.9	0.2
Medicaid Child	420	392	93.3	93.8	93.7	0.1
ACA	1657	126	15.4	8.6	8.5	0.1
EITC	572	459	80.2	78.1	78.1	0.1
CTC	1351	1062	78.6	84.3	84.3	0.0
TANF	74	19	25.7	24.9	24.9	0.0
CCDF	338	85	25.1	25.1	24.9	0.2

A1.6 Measuring Capital Income

TFA requires, as inputs, a pre-tax real rate of return on assets and an assumed annual inflation rate. Following the method detailed in Auerbach et al. (2023), we set the real rate of before-tax return based on the average return on national wealth between 1948 and 2018. This is inferred using data from the National Income and Product (NIPA) accounts and the Federal Reserve's Flow of Funds database. Specifically, the return rate is calculated as the real return on national wealth reported in year t to produce year-t national saving consistent with reported year-$t+1$ national wealth. National saving is total all labor plus asset income (year t national wealth times the inferred year t average real return on this wealth) less total household plus government consumption. In this analysis, we assume, as in Kotlikoff and Summers (1981), that the share of proprietorship and partnership income comprising labor earnings equals the share of national labor income to national income, an approach broadly consistent with the approach taken by Smith et al. (2019), who assume a labor share of 75 percent.[54] We define national wealth as a sum of total household sector net wealth and net financial wealth of federal, state, and local governments. This calculation results in a real rate of return of 6.49 percent. We further assume an inflation rate of 2 percent.

A1.7 Survival-Path Probabilities

As discussed in Auerbach et al. (2023), our survival-path probabilities are constructed from underlying mortality rates estimated by the Committee on the Long-Run Macroeconomic Effects of the Aging US Population (2015). This study sorts Health and Retirement Study (HRS) respondents between 1992 and 2010 by average wage-indexed earnings between ages 40 and 50. For married or partnered couples, average indexed earnings are divided by the square root of 2 prior to sorting. It then estimates post age-50 mortality rates as functions of age and sex.

[54] We define national income at producer prices, not consumer prices as is the NIPA practice.

We follow the same procedure, except we sort SCF respondents based on average wage-indexed earnings from age 25 through age 60.

A1.8 Inflation Indexation

Not all elements of the U.S. fiscal system are indexed for inflation, and those that are adjusted experience different delays and are based on different inflation measures. Where available, 2018 values of fiscal-system components are taken as published. There are nuances to each part of the fiscal system for indexing beyond 2018, however. In describing the indexation in detail below, the specified inflation rate (set to 2%) in simulated years is referred to as $X\%$.

Federal income tax brackets in 2018 equal the official values in that year. 2019 federal income tax brackets are calculated by growing the 2018 brackets by one third times the inflation rate in 2019 ($X\%$) plus two thirds times the Chained Consumer Price Index for All Urban Consumers (C-CPI-U) from the data in 2018.[55] 2020 brackets cannot be calculated using $X\%$ and the 2019 C-CPI-U from the data, however. This is because given that the TFA takes the most recent year of data to be 2018, then, any values of the C-CPI-U from 2019 and onwards do not exist, from the point of view of the TFA. Instead, 2020 brackets are calculated as the 2019 brackets grown by one third times the inflation rate in 2020 ($X\%$) plus two thirds times an imputed C-CPI-U rate for 2019. The imputed C-CPI-U rate for 2019 is calculated by extending the C-CPI-U from 2018 (from the data) by $X\%$, subtracting off a factor, and converting this number to a rate. The factor is constructed such that it maintains the historical difference that has been present between the C-CPI-U and the Consumer Price Index for All Urban Consumers (CPI-U).[56] Tax brackets for $t \geq 2021$ are calculated in the same way: by extending $t-1$ tax brackets by one third times $X\%$ plus two thirds times the imputed C-CPI-U rate for $t-1$. These mechanisms capture indexing lags.

State income-tax brackets for 2018 are also taken as published. Starting in 2019, these brackets are adjusted in the same manner as the federal tax brackets – based on $X\%$ inflation and the same composition of lags. The only difference is that the CPI-U is used in all calculations instead of the C-CPI-U and the subtraction of the factor mentioned in the previous paragraph is unnecessary. The Federal Insurance Contributions Act (FICA) cap and property taxes grow by the specified inflation rate of $X\%$ starting in 2019 with no lag applied.

Indexing Social Security benefits is more complex. These benefits are adjusted using COLAs calculated based on changes to the Consumer Price Index for Urban Wage Earners and Clerical Workers (CPI-W). Published COLAs from the Social Security Administration are used prior to 2018 to determine benefits. Benefits in subsequent years are based on a sequence of imputed CPI-W numbers. To determine this sequence, the following procedure is followed. Calculate the 2018 imputed CPI-W as the 2017 CPI-W from the data, extended by three quarters times the inflation rate in 2017 (the CPI-U in 2017 from the data) plus one quarter times the inflation rate in 2016 (the CPI-U in 2016 from the data). The 2019 imputed CPI-W is calculated by extending the 2018 imputed CPI-W by three quarters times the inflation rate in 2018 ($X\%$) plus one quarter times the inflation rate in 2017 (the CPI-U in 2017 from the data). Iterating this formula forward, the 2020 imputed CPI-W is equal to the 2019 imputed CPI-W, grown by this lagged sum of inflation rates from 2019 and 2018, which are both $X\%$. Thus, from 2020 onwards, the imputed CPI-W is equal to the prior year's imputed CPI-W, extended by $X\%$.

[55] The IRS began indexing federal income tax brackets by the C-CPI-U starting in 2018 with the implementation of the Tax Cuts and Jobs Act (TCJA).

[56] The factor is the average difference of geometric means of the C-CPI-U and CPI-U in years of data they have in common. Subtracting this factor in calculating the imputed C-CPI-U maintains the historical difference between the C-CPI-U and the CPI-U; the C-CPI-U moves in a lower trajectory than the CPI-U.

Now, given this sequence of imputed CPI-W's, the differences between each of these numbers forms the annual COLA adjustment used to determine Social Security benefits.

Medicare Part-B brackets are taken as published from 2018 data. Since the top bracket (which determines if the household must pay the Income-Related Monthly Adjustment Amount, or IRMAA) does not adjust with inflation, the associated income threshold is fixed at \$500,000 and $\$750,000$ for single and joint married filers, respectively. The lower brackets are equal to the 2018 brackets, extended each year by the corresponding year-value in the imputed CPI-W series described above. Therefore, all Medicare Part-B brackets except the top one grow by $X\%$ each year starting in 2020.

Finally, Medicare and Medicaid benefits are indexed. Since these amounts are typically only available for one year, which may not be 2018, the 2018 value is imputed where applicable. This indexing is done using CPI-U data. From 2019 onwards, $X\%$ is used to index benefits. Thus, these benefits are indexed in perfect synchronization with inflation. All other federal and state benefits are also imputed to the 2018 value where applicable by the CPI-U. Starting in 2019, they are extended by $X\%$.

Figure A2: Median Current-Year MTR By Welfare Program Participation Assumption, Ages 20-69

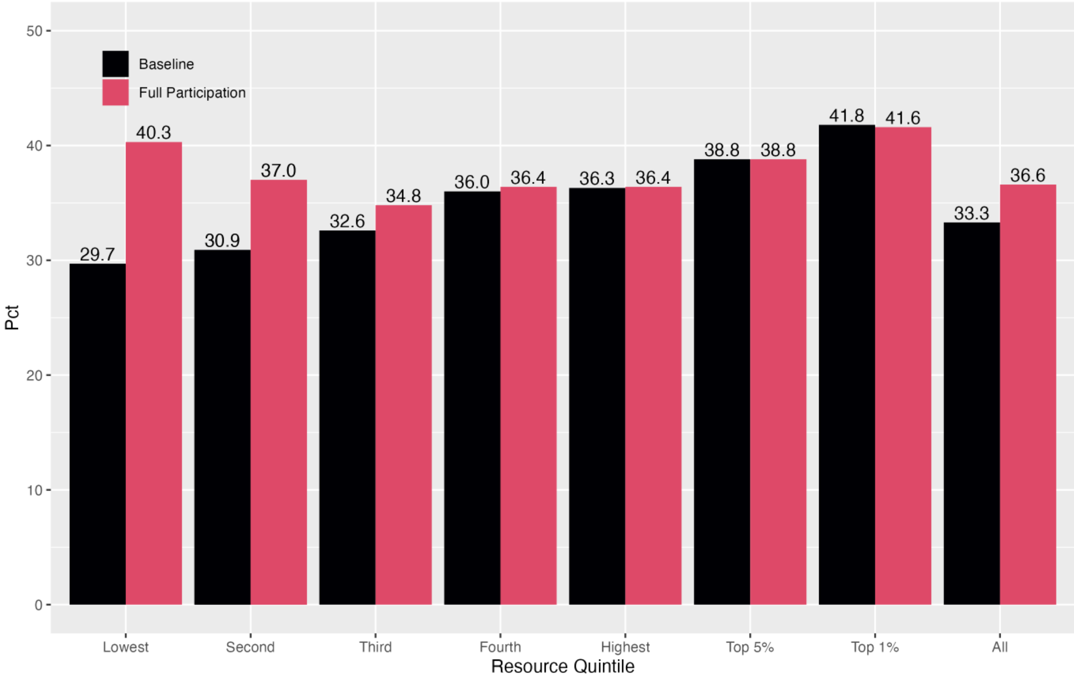


Figure A3: Median Lifetime and Current-Year MTR, Ages 20-29

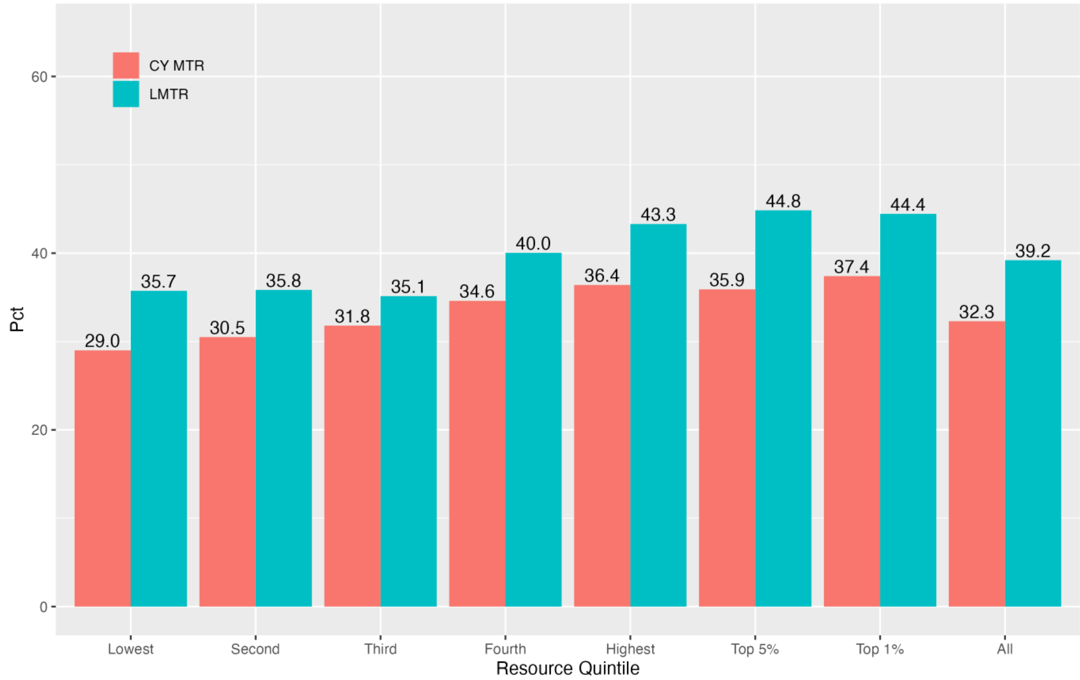


Figure A4: Median Lifetime and Current-Year MTR, Ages 30-39

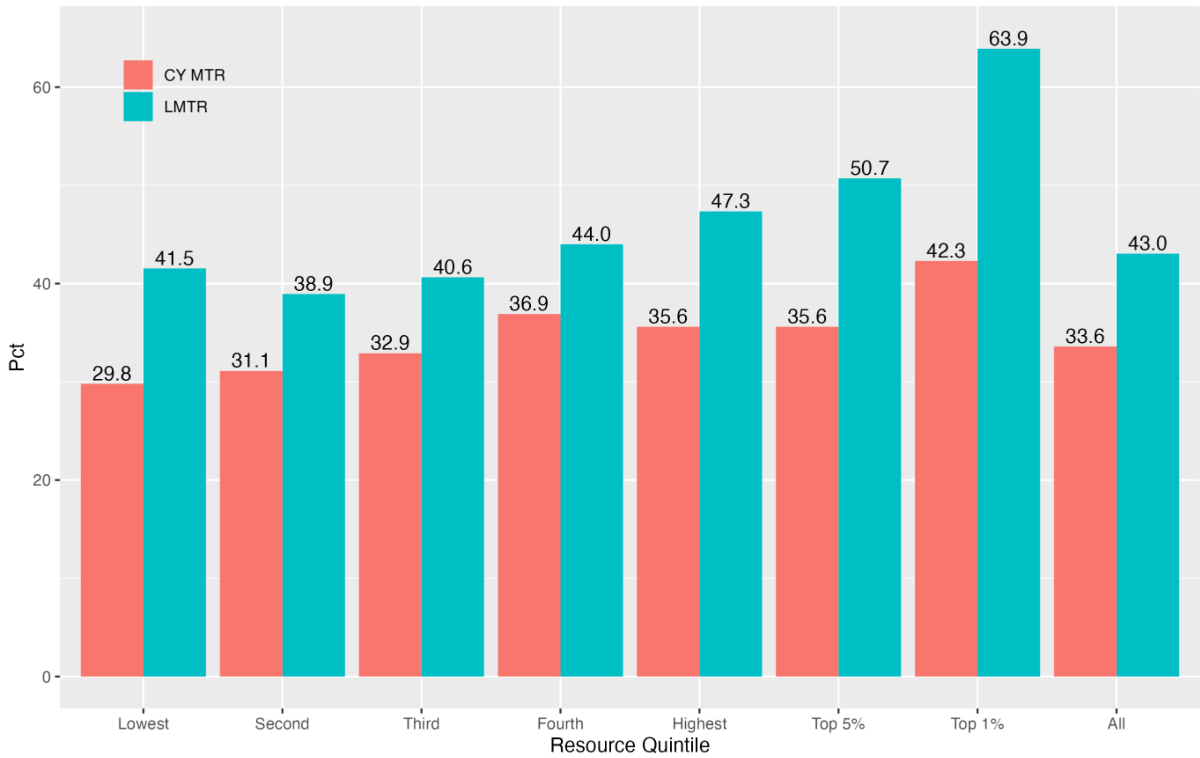


Figure A5: Median Lifetime and Current-Year MTR, Ages 40-49

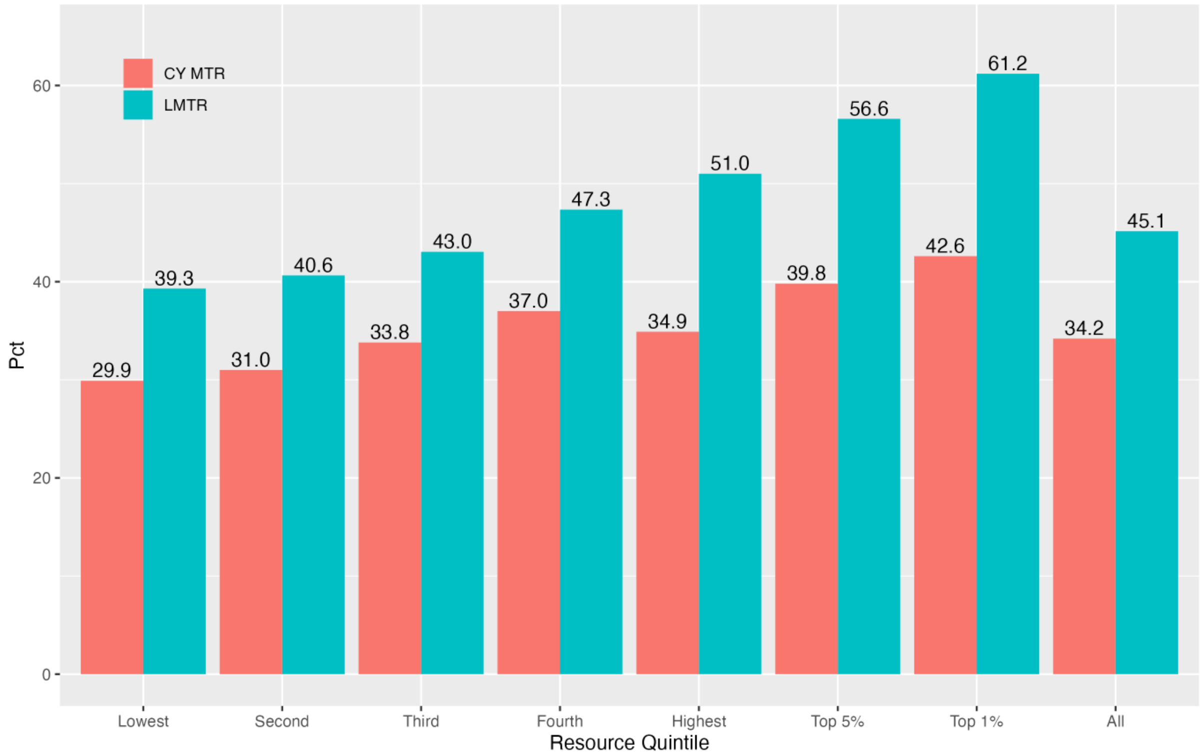


Figure A6: Median Lifetime and Current-Year MTR, Ages 50-59

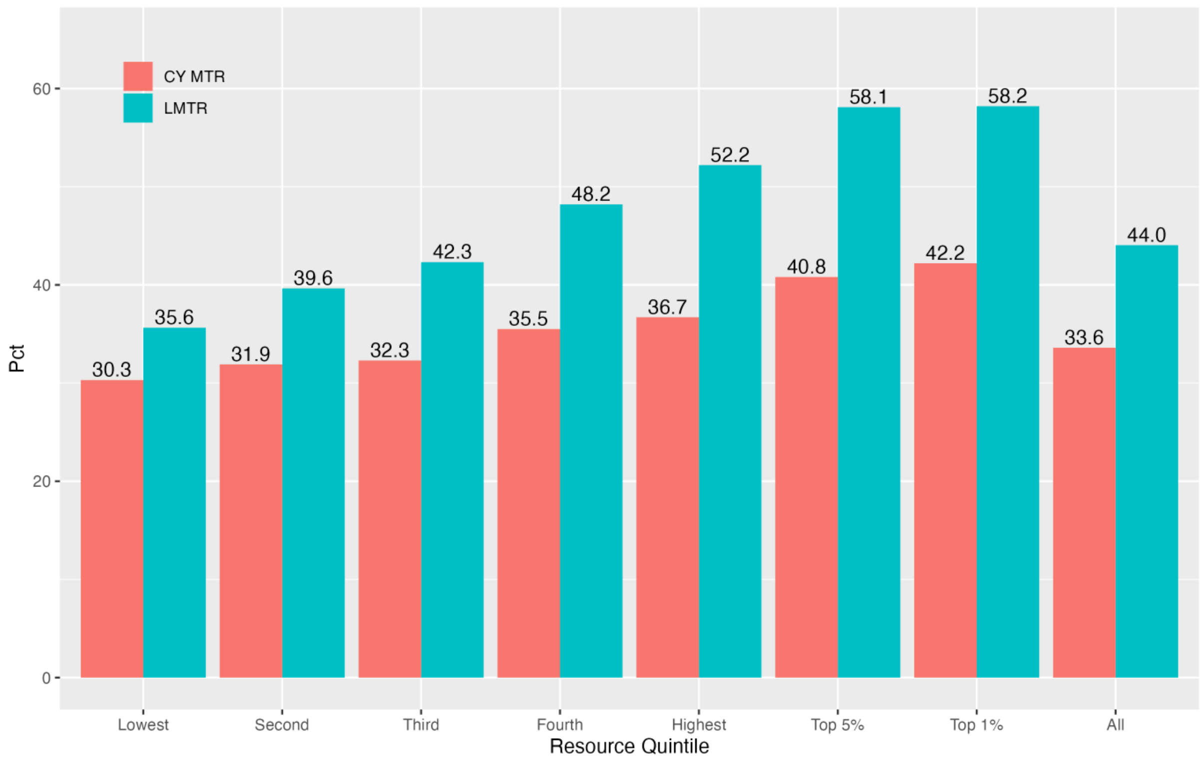


Figure A7: Median Lifetime and Current-Year MTR, Ages 60-69

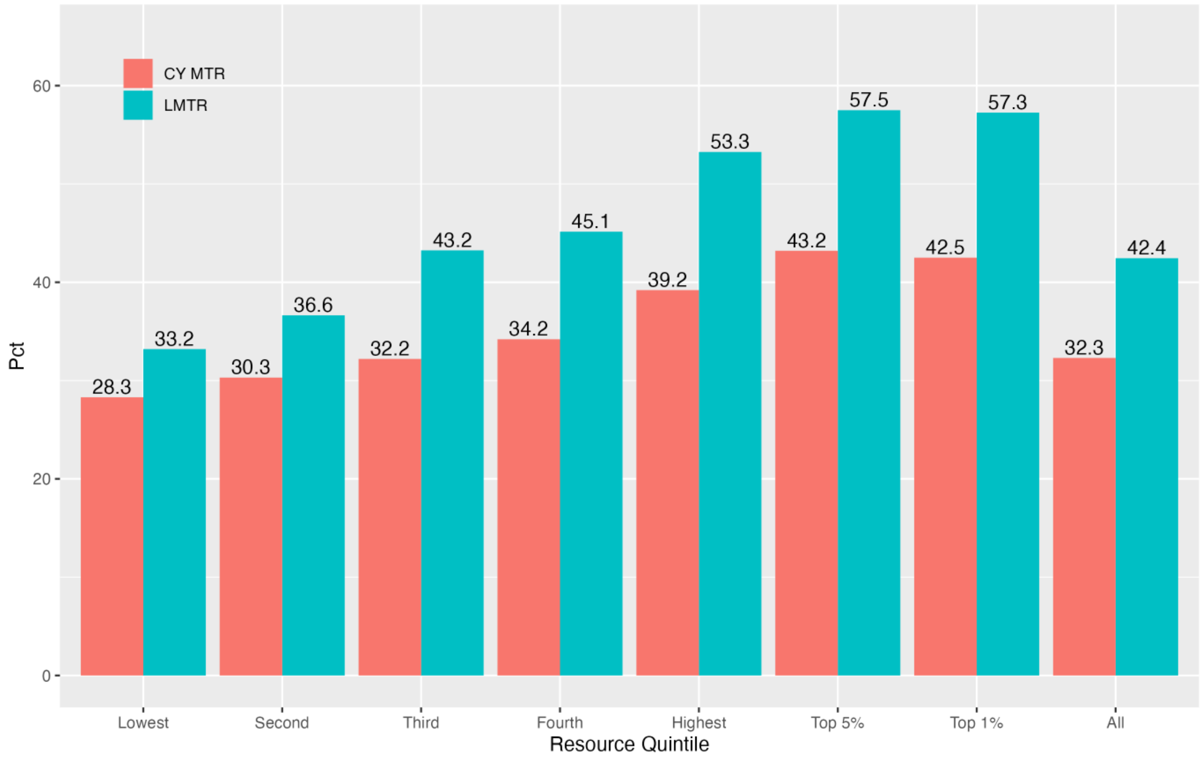
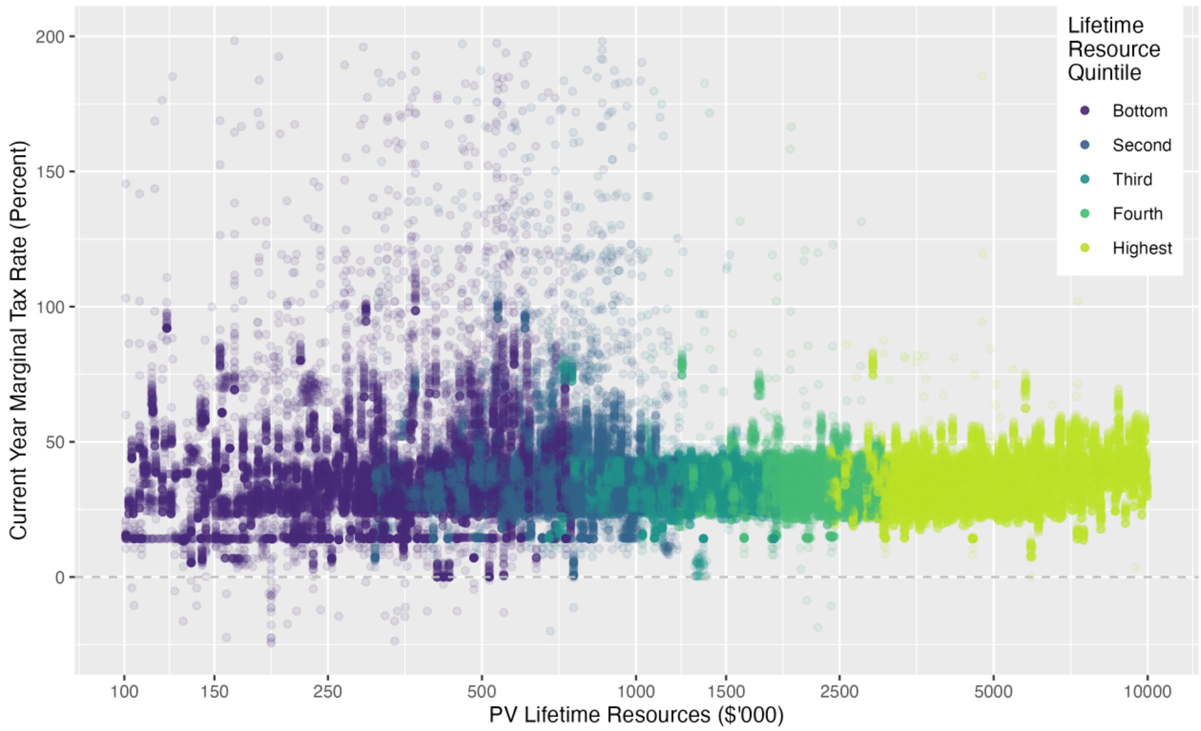


Figure A8: Current-Year Marginal Tax Rates from $1,000 Earnings Increase in Current Year, Ages 20-69



Plot filtered to SCF households with PV lifetime resources between $100,000 and $10 million

Figure A9: Lifetime Marginal Tax Rates from $1,000 Earnings Increase in Current Year, Ages 20-69, Full Welfare Participation

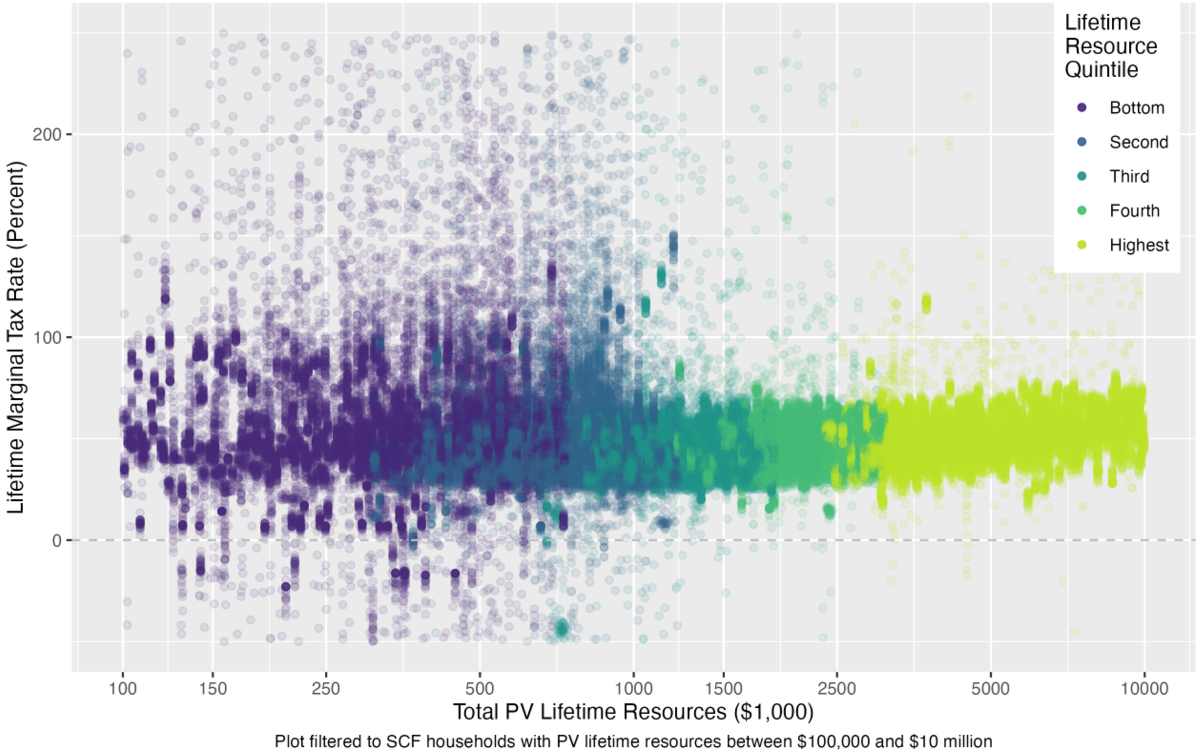


Figure A10: Current-Year Marginal Tax Rates from $1,000 Earnings Increase in Current Year, Ages 20-69, Full Welfare Participation

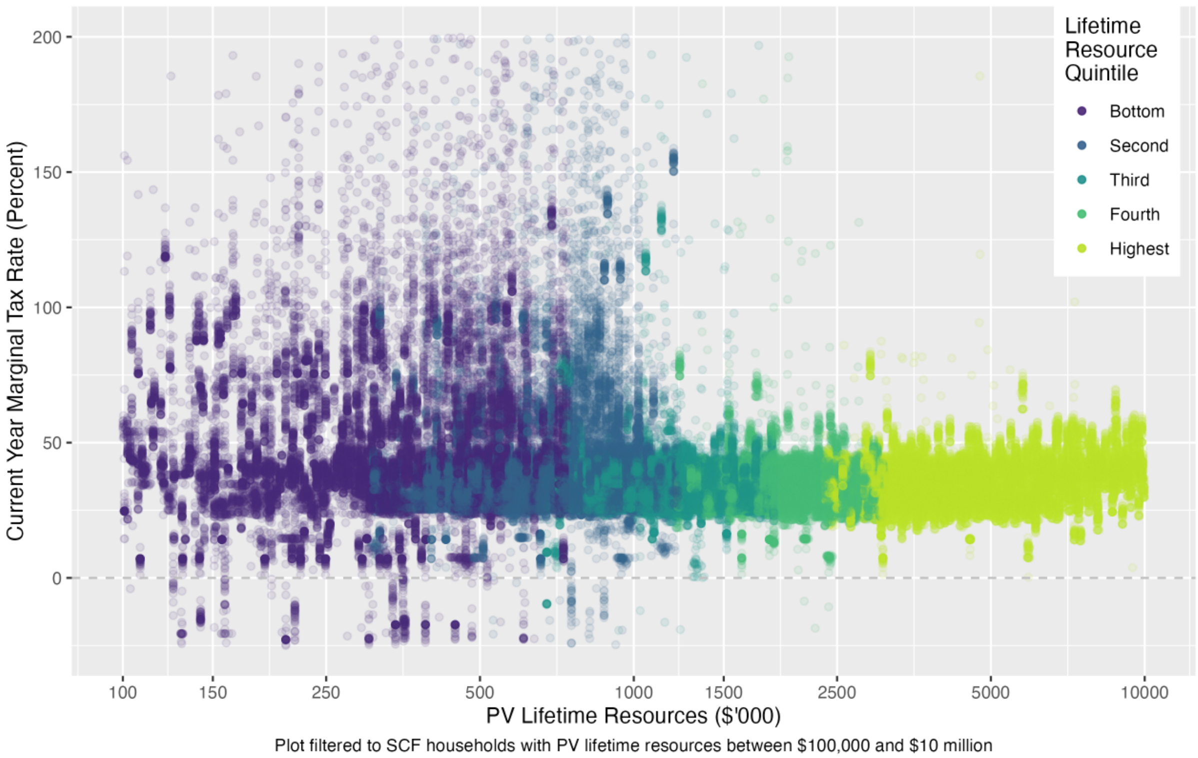
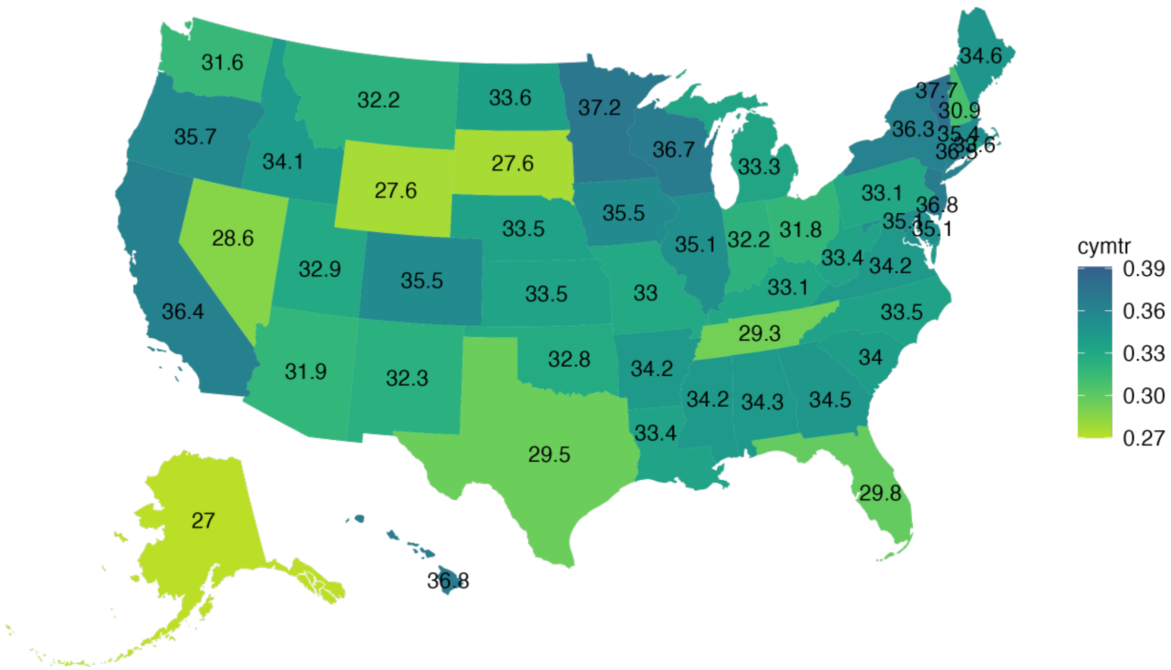


Figure A11: Cross-State Variation in Median CMTRs (Age 30-39, Lowest Resource Quintile)



(a) Note: This measure of marginal tax rates is based on the $1,000 increase in the current-year earnings

Figure A12: Difference Between Highest and Lowest State LMTR from $1,000 Earnings in Current Year, Ages 20-69

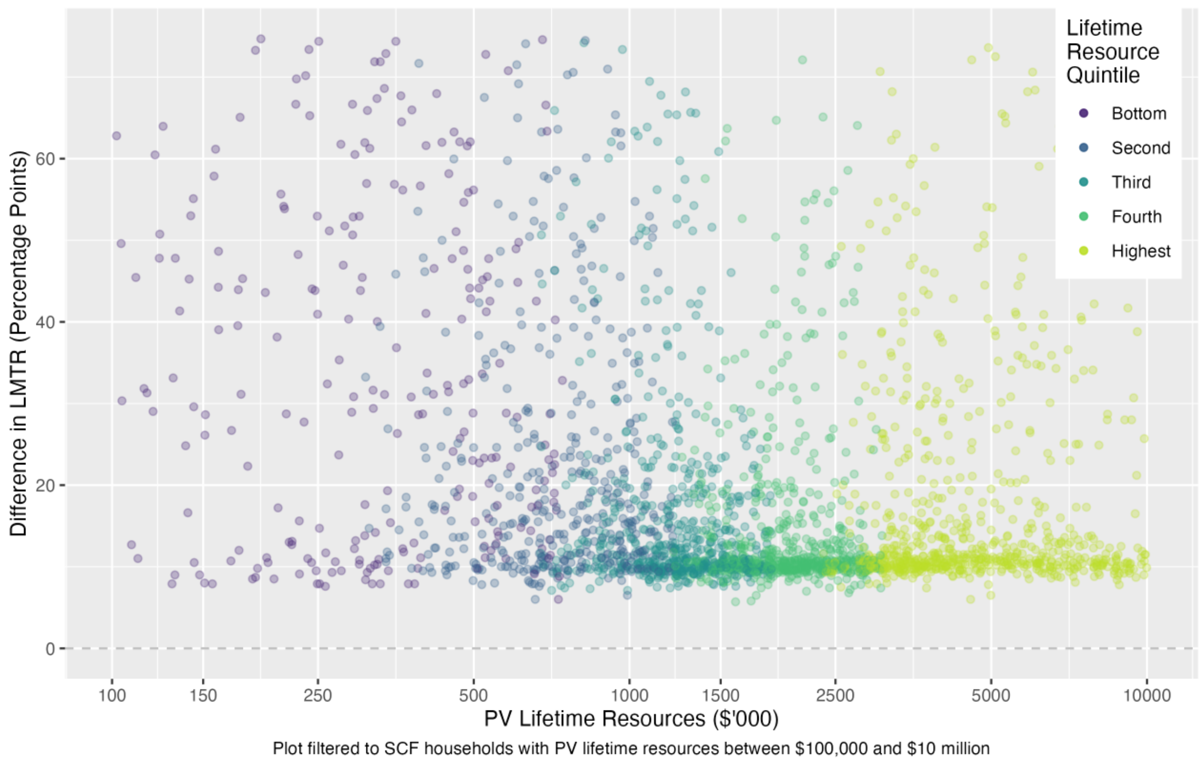


Figure A13: Median CMTR by Amount of Added Income, Ages 20-69

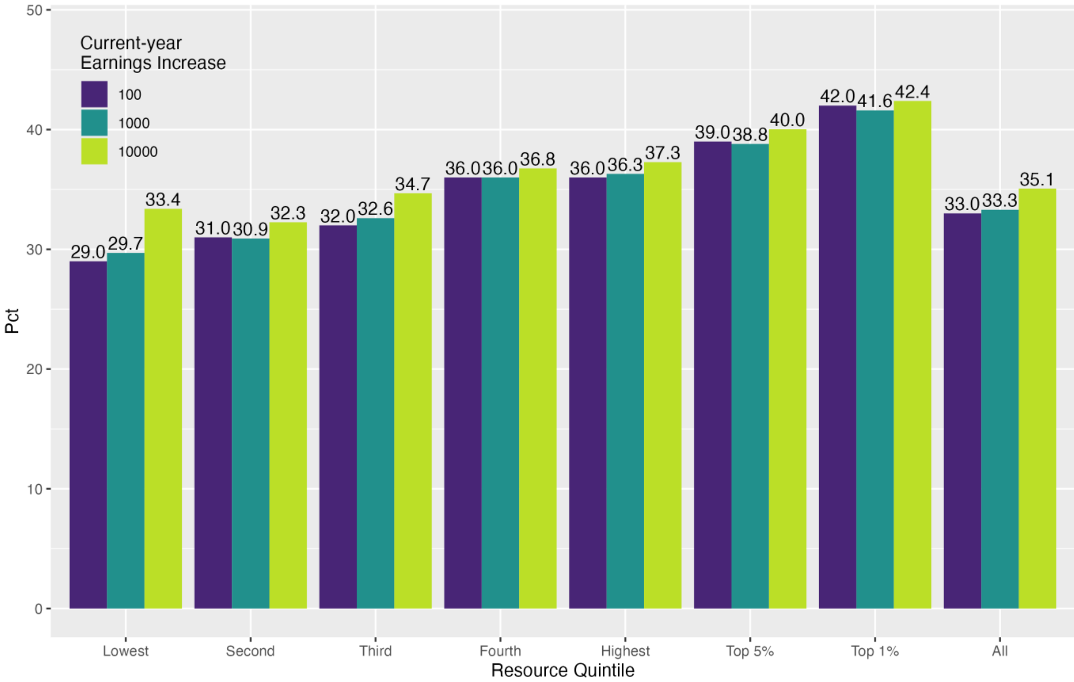


Table A6: Summary Statistics for Marginal Tax Rates, Age 20-69, Full Participation

Lifetime Marginal Tax Rates

Resource Group	q25	median	mean	q75	q90	std.dev
Bottom	34.8	48.8	55.2	68.7	99.2	636.1
Second	35.7	43.5	52.1	53.6	72.4	282.8
Third	36.1	43.0	50.5	49.9	56.4	119.8
Fourth	40.4	45.5	46.2	52.7	58.3	49.4
Highest	42.9	49.2	50.2	57.2	64.2	18.3
Top 5%	46.6	54.7	54.1	61.7	67.5	21.3
Top 1%	50.1	57.9	55.8	65.0	69.7	16.5
All	38.6	45.7	50.8	55.0	66.4	288.3

Current-Year Marginal Tax Rates

Resource Group	q25	median	mean	q75	q90	std.dev
Bottom	28.7	40.3	42.0	57.9	86.7	145.3
Second	30.0	37.0	45.1	42.9	66.3	142.1
Third	29.9	34.8	38.4	39.3	42.0	84.6
Fourth	31.3	36.4	35.7	39.7	42.0	14.5
Highest	30.1	36.4	35.9	41.0	44.6	8.7
Top 5%	33.6	38.8	38.4	43.1	47.8	8.4
Top 1%	37.3	41.6	40.8	45.2	50.1	8.7
All	30.1	36.6	39.4	41.3	52.9	89.1

Table A7: Median LMTRs by Resource Group and No. of Children

No. of Children	Bottom	Second	Third	Fourth	Highest	Top 5%	Top 1%	All
0	37.0	40.3	44.5	48.1	55.0	57.4	57.8	46.6
1	41.5	37.1	37.4	44.9	52.6	56.9	57.9	45.1
2	44.9	39.1	36.5	43.3	52.9	58.7	60.7	45.5
3+	39.7	34.4	33.2	41.9	53.8	58.6	59.8	43.2

All children included are age 17 or less as of 2018. Unless otherwise specified by policy (e.g. children under age 22 living with parents count toward the parents' SNAP eligibility), we assume that children leave home and stop being dependents at age 19.

Table A8: Breakdown of LMTR and CMTR sources from Part-time Labor Force Entry, Pre-Retirement Age, Bottom Resource Quintile, Non-working SCF Households

	C Baseline	C Marg.	C Diff	L Baseline	L Marg.	L Diff
Federal Income Tax	1,689	3,713	2,024	15,486	37,585	22,099
State Income Tax	149	425	276	1,195	4,154	2,960
Other Taxes	351	1,036	685	15,236	22,406	7,170
Total Taxes	2,189	5,174	2,985	31,917	64,145	32,228
SNAP	1,765	1,017	-748	17,855	9,632	-8,223
TANF	146	26	-120	459	85	-374
Section 8	820	574	-246	11,433	8,300	-3,133
CCDF	364	317	-46	1,210	1,004	-205
Social Security	0	0	0	66,966	72,913	5,947
SSI	322	122	-200	10,236	4,537	-5,699
Medicaid	2,538	2,085	-452	30,445	25,491	-4,954
ACA	722	752	30	9,168	9,204	36
Other Transfers	1,318	1,098	-220	56,987	53,237	-3,750
Tot. Transfer Payments	7,994	5,991	-2,003	204,759	184,404	-20,355
Net Taxes	**-5,805**	**-817**	**4,988**	**-172,843**	**-120,259**	**52,583**
Added Income	0	15,000	15,000	0	145,325	145,325

Table A9: Measure of State-Level Total Spending Dispersion

	q25	median	mean	q75	q90	st.dev
Bottom	18.4	26.6	36.2	47.7	69.0	27.7
Second	11.5	17.2	28.8	34.4	63.9	29.4
Third	10.9	14.6	25.6	24.9	52.2	35.1
Fourth	11.9	14.0	17.2	17.1	27.7	11.5
Highest	13.5	15.5	16.2	17.6	21.4	8.5
Top 5%	13.5	16.2	16.8	18.7	21.6	10.6
Top 1%	12.3	17.6	17.5	21.6	26.0	9.0
All	12.1	15.2	21.9	21.2	38.1	21.5