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 work incentives and disincentives. This paper uses the Fiscal Analyzer (TFA) to assess how these policies, in unison, impact work incentives. TFA is a life-cycle, consumption-smoothing program that incorporates cash-flow constraints, retirement hazards, all major federal and state fiscal policies, and welfare-program-specific take-up rates. We use TFA in conjunction with the 2019 Survey of Consumer Finances to calculate Americans' remaining lifetime marginal net tax rates (LMTR). Our findings are striking. Over half of working-age Americans face LMTRs exceeding 40 percent. One in four households in the bottom lifetime resource quintile face LMTRs above 50 percent. One in ten face rates above 70 percent, effectively locking them out of the labor force and into poverty. The richest 1 percent also face extremely high LMTRs with a 57.9 percent median rate. We find remarkable dispersion in both LMTRs and current-year marginal tax rates, not only across, but within states, age cohorts, and resource quintiles. Among those in the bottom quintile, 5.1 percent face LMTRs exceeding 100 percent; 4.5 percent face negative rates. Based on simplified excess burden calculations, eliminating the dispersion in marginal lifetime net taxation would produce efficiency gains of up to 24.1 percent of labor income for households in the bottom quintile where MTR dispersion is greatest.

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1 Introduction

A host of federal and state tax and benefit policies jointly determine Americans' incentives to work. Adopted with apparently little concern for their collective impact on work incentives, many of these policies are extraordinarily complex, rendering lifetime budget constraints highly non-linear and non-convex. The source of these non-linearities and non-convexities are intertwined and often arcane provisions that condition tax payments and benefit receipts on labor income, asset income, total income, household demographics, and the level of assets.

Social Security typifies our fiscal system's complexity. It has 2,728 primary rules governing the receipt of its 12 benefits, plus tens of thousands of secondary rules circumscribing these main rules.[1] Fiscal system non-convexities are ubiquitous. Earn \$1 too much two years back, and your Medicare Part-B premiums can rise by \$1,187. Earn or save \$1 too much and, depending on the state, lose thousands of dollars in your own or your family members' Medicaid benefits. Hold \$1 too much in assets and forfeit thousands in Supplemental Security Income (SSI). Earn an extra dollar in a Medicaid non-expansion state and receive thousands of dollars in otherwise unavailable ACA subsidies. Earn \$1 beyond Social Security's earnings ceiling and your Social Security payroll tax rate drops to zero. Earn \$1 too much and, depending on your income, lose up to 21 cents in the Earned Income Tax Credit (EITC). Earn too little relative to your spouse and receive nothing based on your Social Security contributions. Earn more and an extra dollar of contributions can produce several dollars more, measured in present value, in lifetime benefits. The list goes on.

The principal provisions of our federal and 42 state (including Washington, D.C.) personal income-tax systems are intricate enough. But they also embed special benefit programs, like the EITC, the Child Tax Credit, and the Child and Dependent Care Tax Credit, as well as special tax systems, including the Alternative Minimum Tax, the taxation of Social Security benefits, high-income wage and asset Medicare taxes, and special treatment of capital gains and dividends as well as other types of asset income. Moreover, most of our "federal" benefit programs are state specific insofar as many states supplement some, if not all, federal benefits while imposing additional rules and program requirements. The list includes Medicaid, the Affordable Care Act, TANF, SNAP, Housing Assistance, Child Care Assistance, and Energy Assistance.

The morass of programs comprising our fiscal system motivate this paper's central questions: What are the typical levels of marginal net tax rates facing Americans of different ages and resource levels, taking full account of all additional current and future net taxes, measured in present value,arising from extra initial earnings? How different are these lifetime marginal net tax rates (LMTRs) within and across age and resource groups? Is the fiscal system locking many of the poor into poverty by confronting low-income households with extraordinarily high work disincentives? How much does future taxation matter? I.e., how much higher are LMTRs than current-year marginal net tax rates (CMTRs)? How much does one's choice of the state in which to live impact one's 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? And how large is the excess burden arising from the dispersion in marginal net taxation?

We address these questions by running respondents to the 2019 Survey of Consumer Finances (SCF) through The Fiscal Analyzer (TFA), a life-cycle consumption-smoothing software tool.

[1] These rules include the intricate, partially indexed calculation of basic benefits, maximum family benefit provisions, reductions for taking benefits early, increases for taking benefits late, earnings testing of benefits received prior to full retirement, an adjustment at full retirement of benefits lost to the earnings test, annual re-computation of basic benefits in light of additional earnings, special rules governing benefits for divorcees and widow(er)s, five distinct widow(er) benefit formulas, and benefit reductions affecting those receiving non-covered pensions.

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.[2] To better capture marginal tax rate dispersion, we augment SCF data with respondent-specific earnings growth, retirement hazards, welfare program take-up behavior, and survival-path probabilities estimated using 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.

As for the last question, a worker's LMTR and CMTR can differ due to the "double taxation" of labor earnings. For households that aren't so severely borrowing constrained so as to spend all cash on hand in the current year, additional earnings lead to additional saving and, thus, additional future assets. This, in turn, means higher future taxable asset income and total income and, consequently, higher future asset-income taxation (e.g., Medicare's high-income asset-income taxation), higher future federal and state total-income taxation, including sales taxation, and, potentially, lower income- and asset-tested future benefits. Since additional current earnings lead to additional future net taxes, proper measurement of marginal net tax rates on current labor supply must account for the present value of future as well as current net taxes.

Of comparable importance is taking into account benefit-program non-participation. LMTRs can be remarkably high as it is. But far more households, particularly low-income households, would face even larger LMTRs and CMTRs were they to participate in all benefit programs for which they are eligible. As described below, we go to considerable lengths to appropriately attribute program-participation behavior to our SCF respondents.

Our study is intentionally limited in a critical dimension. We seek to understand Americans' work disincentives, not their responses to those disincentives. While a number of past studies have considered behavioral responses[3], we leave such analysis for future research. Hence, we measure remaining-lifetime and current-year net taxes resulting from either temporary or permanent, exogenous increases in labor earnings. Doing so lets us abstract from differences in household labor-leisure preferences. Were we to study not just the impact of the fiscal system on intertemporal budgets, but the reaction to them, we'd necessarily need to decompose provisions and reactions to understand which was at play. Hence, this paper is a necessary first step toward a full evaluation of the impact of the U.S. fiscal system on labor supply. This said, we do present a simple excess burden calculation that considers the potential deadweight loss arising from only the dispersion of distortions of workers' current-year labor-leisure choices.

Our main findings, which focus on the fiscal consequences of 2019 SCF household heads earning $1,000 more in our base year, 2018, are striking. Over half of working-age Americans face LMTRs exceeding 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 even greater with full welfare program participation. The richest 1 percent (measured by resources – net wealth plus human wealth) also face extremely high LMTRs with a 57.9 percent median value.

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 remaining lifetime resources, LMTRs can be far higher than CMTRs. For the richest 1 percent of 40-49 year-olds, for example, the respective median LMTR and CMTR are 62 percent and 42.6 percent. We also find remarkable dispersion in both LMTRs and CMTRs for any given level of lifetime resources,

[2]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.

[3]For an excellent review of this literature, see Moffitt et al. (2012).

but particularly among the poor. There are also major differences in LMTRs and CMTRs across states.

Unlike predictions of marginal tax rates by Diamond (1998) and Saez (2001), we find no evidence of 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 working-age Americans of the bottom lifetime 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 those in the top 1 percentile of lifetime resources. These resource-percentile differences in marginal tax rates indicate how work disincentives differ among the rich, middle class, and poor. But they don't tell us about fiscal progressivity, which depends on average, not marginal lifetime net tax rates. As shown in Auerbach et al. (2023), average lifetime net tax rates rise sharply with lifetime resources, rendering the U.S. fiscal system highly progressive. Here, though, we measure and compare work incentives, not fiscal burdens.

The absence of U-shaped marginal net taxation is a consequence of partial welfare program participation. As section 6.1 shows, assuming, counterfactually, full benefit-program participation, a clear U-shaped pattern of LMTRs and CMTRs emerges.[4] Assuming full participation, the median LMTR in the bottom resource quintile is 48.8 percent. This rate is more than 10 percentage points above that of partial participation and comparable to the top quintile's (partial or full participation) rate of 49.1 percent. The median CMTR would be 40.3 percent instead of 29.7 percent.

Both current and lifetime rates 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 percentile values of the remaining lifetime marginal net tax rate are 27.2 percent, 41.5 percent, and 51.9 percent, respectively, with minimum and maximum rates of -14,983.6 percent and 18,449 percent. For this age cohort, the standard deviation in LMTRs is almost fifty times larger for the bottom than for the top resource quintile. For bottom-quintile workers, our current-year labor supply excess burden calculation produces a huge efficiency loss – roughly one quarter of labor earnings.

In addition to the net tax on marginal labor supply, the fiscal system contains significant work-participation disincentives. For many working-age Americans, the labor-supply options may simply comprise not working, working part time, and working full time. Accordingly, we consider SCF respondents who are of working age, but aren't currently employed, and calculate the lifetime and current-year net taxes they'd pay, respectively, as a share of their lifetime and current-year compensation from working either part or full time. We find that net LMTRs equal nearly 50 percent for lower-resource workers contemplating full-time work and nearly 40 percent for part-time work. Interestingly, for high-resource households, the net lifetime tax on full-time work is even higher – 51.7 percent for the top quintile. Current-year participation net tax rates are roughly 10 percentage points lower. One's choice of state in which to live 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

[4] Diamond (1998)'s and Saez (2001)'s demonstration that optimal income taxation requires higher marginal net taxation at the bottom, lower in the middle, and higher at the top reference Mirrlees (1971). The intuition is simple. For high earners, high tax rates on low levels of earnings effectively represents an implicit and efficient lump-sum tax. This provides enough inframarginal revenue to more than compensate low earners for having to live with major work disincentives. Stated differently, the optimal tax entails high negative average as well as high positive marginal taxation of the poor. Unfortunately, Diamond and Saez didn't incorporate non-participation in their analyses. Non-participation reflects inertia and stigma as well as a reluctance to deal with multiple benefit programs (see (Riphahn 2001; Yaniv 1997)) and bureaucratic management of such programs. The feature common to virtually all U.S. fiscal programs is complexity, with penalties for failure to fully comply adding to the participation barriers.

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.

The next section briefly reviews prior studies measuring fiscal work incentives and disincentives. Section 3 presents our remaining lifetime framework. This section and others describing our methodology borrow heavily and, in some cases, verbatim, from Auerbach et al. (2023), Altig et al. (2022), and other prior studies. Section 4 describes TFA, including its calculation method and the various means by which we confirm its calculations are precisely accurate. Section 5 describes our methods for allocating SCF households to states, imputing both past and future labor earnings, determining survival probabilities based on respondents' levels of current and past imputed earnings, imputing retirement ages, and adjusting for partial benefit-program take up. Section 6 presents our nationwide findings. Section 7 estimates the cost of labor force entry of non-working households. Section 8 considers differences across states in marginal net taxation. Section 9 presents a simple excess burden calculation. Section 10 concludes.

2 Prior Studies

Over the years, numerous papers have produced different measures of marginal tax rates. One of the earliest studies is Joines (1981), which used data from the IRS Statistics of Income and other sources, benchmarked to National Income Account totals, to compute marginal tax rates on labor and capital income from 1929 to 1975. Like our study, Joines took account not only of income taxes at the federal level, but also other federal taxes and a range of state and local taxes. However, his estimates of marginal tax rates were based on differences in tax liabilities for successive income groups, rather than for individuals, and ignored transfer programs with their implicit taxation. Seater (1982) and Seater (1985) take a similar approach for estimating gross, not net marginal tax rates across income groups based on observed tax payments.

An oft-cited paper by Barro and Sahasakul (1983) takes a different approach, using tax rate schedules rather than actual tax payments to estimate marginal tax rates. The authors argue that actual deductions and other methods of reducing individual tax liabilities differ from those dictated by the rate schedule alone and involve tax avoidance costs that may vary across individuals, which are ignored in looking simply at reduced tax liabilities based on the tax schedule. We deal with such unobserved characteristics by assuming a uniform objective of consumption smoothing across households, common portfolio decisions within groups with respect to tax-favored saving, and other assumptions that eliminate the potential effects of unobserved preference heterogeneity on marginal tax rates. Unlike Joines (1981), Barro and Sahasakul consider only the individual income tax in estimating marginal gross tax rates. However, they also note the importance for welfare analysis of marginal tax rate dispersion and consider the dispersion of marginal tax rates, showing the distribution of these tax rates for each year between 1961 and 1980.

Using the statutory income tax rate schedule – the bracket values – to estimate marginal tax rates is problematic since the effective income tax schedule is also affected by special provisions based on the type of income, so that the "full" marginal income tax rate may differ quite substantially from the statutory income tax rate. Examples include phase-outs in the exclusion of social security benefits from the income tax, increases or decreases in the Earned Income Tax Credit (EITC), as well as floors and ceilings on various income tax deductions, such as medical expenses and charitable contributions. Barthold et al. (1998), for example, show how considering 22 such income tax provisions affected federal marginal income tax rates prevailing in 1998.

Like these authors, we rely on the full income tax rules, rather than just the statutory tax rates, in computing marginal tax rates. However, we don't limit ourselves to the income tax. As indicated, we consider the entire U.S. fiscal panoply of federal and state fiscal programs in measuring LMTR and CMTR. The importance of doing so was emphasized by Shaviro (1999). He estimated current-year marginal net tax rates for representative low-income individuals, taking account of the effects of additional income on the receipt of various transfer benefits, including Tax Assistance for Needy Families (TANF), housing assistance, Medicaid, and the Supplemental Nutrition Assistance Program (SNAP). Shaviro showed that such individuals may face extremely high marginal tax rates as a consequence of income-induced benefit loss.

One particularly important cause of the deviation of marginal tax rates from those in the tax schedule, at least historically, was the Alternative Minimum Tax (AMT). Feenberg and Poterba (2004) analyze the importance of this provision and how marginal tax rates would have been affected by its reform, an issue relevant to how one analyzes the effects of the 2017 Tax Cuts and Jobs Act, which substantially reduced the impact of the AMT.

While the literature discussed thus far focuses on measuring marginal income tax rates, a significant focus of our analysis is on the marginal tax rates associated with benefit programs, especially among lower income individuals who are major recipients of such benefits. Recent work by authors at the U.S. Department of Health and Human Services (HHS) estimates marginal tax rates taking account of the most important tax and transfer programs.[5] Using microdata from the Current Population Survey and the Urban Institute's Transfer Income Model, Version 3 (TRIM3), this research, like ours, considers taxation at the individual level and examines not just average or median marginal tax rates, but also the dispersion of marginal tax rates.

Another recent study by the Congressional Budget Office (CBO 2015) also 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 Affordable Care Act. 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 (2017) find more dispersed and higher median marginal tax rates among those just above the federal poverty line, but they estimate that the problem of very high marginal tax rates among the poor, including rates possibly 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. Similar to Kosar and Moffitt, we base our marginal tax rate estimates on actual program take-up, rather than eligibility.

We go beyond the studies just mentioned in a number of ways. First, we consider all major federal and state tax and benefit programs, taking into account all state-specific provisions. Table 1, which lists these programs, indicates which programs differ by state. For example, there are 42 distinct state income tax systems and 51 distinct state-specific Medicaid programs. All told, our study considers over 500 fiscal programs, each in full detail.[6] Second, we study the entire population, not just those with low and moderate incomes, to assess the full distribution of marginal tax rates.

Third, we consider how marginal tax rates vary by age cohort and other demographic attributes. Fourth, we go beyond current-year calculations to consider the effects of current income

[5]See, for example, Giannrelli et al. (2019) and Macartney and Chien (2019). Work arising from the HHS marginal tax rate project is published at https://aspe.hhs.gov/marginal-tax-rate-series.

[6]This programming was not an academic exercise conducted subject to a publication deadline and based on limited resources. Instead, the coding underlying our result was done, as well as updated, over multiple years by a professional software company, Economic Security Planning, Inc. (ESP). ESP was able to assign five professional software engineers to the project on a full-time basis thanks to significant funding from the Sloan Foundation and the Federal Reserve Bank of Atlanta.

on the full present value of net taxes. In so doing, we follow the work of Gokhale et al. (2002) and Kotlikoff and Rapson (2007) who make initial forays into properly measuring LMTRs. They incorporate a limited number of tax and benefit programs, ignore state-specific fiscal policy, and consider only a handful of stylized households. They also ignore alternative survival paths, bequests, and estate taxes. Finally, they consider the fiscal system as it existed roughly twenty years ago, while our study is based on tax codes as of 2018.

3 Our Remaining Lifetime Framework

Consider any potential survival path, i. Along that path, the realized present value of total remaining lifetime discretionary plus non-discretionary spending, including bequests, denoted 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 $i's$ realized present value of future labor earnings, H_i. I.e.,

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

The expected remaining lifetime present values of spending, 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

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

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

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

The LMTR incorporates future as well as current net taxes. Therefore, it can differ, potentially significantly, from the analogous current-year calculation, CMTR. And since the size of T will differ across households based on the level of each household's resources and the age-related extent to which the household's resources comprise human versus non-human wealth, 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.[7] As for the current-year marginal net tax rate, we simply form the ratio of additional current-year net taxes to $1,000. In addition to measuring marginal net taxation arising from a one-time $1,000 increase in earnings, we also consider marginal rates arising from a full-time or part-time job, paying $15 an hour, for respondents currently out of the labor force.

4 The Fiscal Analyzer

The Fiscal Analyzer (TFA), developed in Auerbach et al. (2017), Altig et al. (2020), and Auerbach et al. (2023), is a life-cycle, consumption-smoothing tool that incorporates borrowing constraints and all major federal and state fiscal policies. These policies are listed in table 1. Detailed TFA documentation is available at Kotlikoff (2019). To abstract from preferences, TFA assumes that households smooth their living standards – discretionary spending per household member adjusted for economies in shared living and the relative cost of children – to the maximum extent possible without borrowing (or, if already indebted, additional borrowing).[8] This behavior is consistent with Leontief intertemporal preferences over the household's future living standard.[9]

Table 1: 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.

The relationship between a household's discretionary spending in year t, C_t, and its under-

[7] 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.

[8] Discretionary spending is all household outlays apart from taxes, housing expenses, repayment of loans, and in-kind consumption transfers, such as Medicare and Medicaid benefits. Also, note that households can experience a number of borrowing constrained intervals as they age along a given survivor path.

[9] Note, TFA can accommodate any desired age-living-standard profile. Our uniform assumption of a flat profile as opposed to one that, for example, gradually declines after, say, age 75 does not materially alter our results. Although we assume households desire a perfectly smooth living standard per household member through time, 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-constraint interval.

lying living standard per effective adult, c_t, is given by

$$C_t = c_t(N + .7K)^{.642}, \tag{10}$$

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.[10]

TFA inputs or provides default values for the following data: marital status, birth dates of each spouse/partner, birth dates of children, current-year labor earnings, current regular and retirement account (separately treated tax-deductible and Roth) asset balances, current and projected future contributions to each type of retirement account, retirement-account withdrawal start dates, Social Security retirement-benefit collection dates, defined benefit pensions, housing expenses, real estate holdings, household debts, rates of return on assets, and the inflation rate.

4.1 TFA's Solution Method

TFA uses dynamic programming to smooth each household's living standard per equivalent adult (the c_ts), subject to borrowing constraints. The program simultaneously calculates not just the household's smoothest living standard path if both the household head and spouse/partner live to their maximum ages, but also the household's year-specific demands for life insurance (and, thus, the life insurance premiums it will pay each year) to ensure that survivors have at least the same living standard as would otherwise have been the case.[11] The program also determines each of the household's above-referenced taxes and transfer payments along each of its potential survivor paths.

The problem TFA solves is computationally challenging for four reasons. First, there is the curse of dimensionality arising from the TFA's tens of thousands of survivor-path-specific state asset variables. These are the levels of regular as well as spouse/partner-specific tax-deferred and Roth retirement accounts in each survivor state. Take, for example, a 40 year-old couple that could live to 100. They have over 200,000 survivor contingent regular and retirement account state variables. One example is the regular, tax-deferred and retirement account assets of the widow at age 69 if the husband dies at 51. Second, there are a multitude of survivor paths in the case of younger couples. And taxes, transfer payments, discretionary spending, and life insurance holdings must be separately determined for all years for each survivor path. Third, spending, insurance amounts, and net taxes on any survivor path are interdependent. Indeed, they are also interdependent across paths. Hence, one needs a simultaneous equations solution. Fourth, the program needs to run in finite time.

TFA's computation method, for which it received a patent, entails iterating between three dynamic programs: one that smooths consumption assuming household heads and spouses/partners reach their maximum ages of life, one that determines annual life insurance needs for the household heads and their spouse/partner, and one that determines annual net taxes assuming no early death.

Each program takes the output of the other programs as inputs. To ensure precision to many decimal places, TFA utilizes a sparse grid method between iterations to narrow its grids to

[10] To repeat, TFA's default assumption is perfect living-standard smoothing. But the program can be run with any desired age-living-standard path. It can also run with any age-specific child-equivalency factors, and any degree of economies in shared living. The program can also be run assuming any maximum age of life. In this study, we assume a maximum of age 100.

[11] TFA generates positive life insurance holdings only for years when the insured's death would leave survivors with a lower living standard than they were experience were both the household head and spouse/partner to live to their respective maximum ages of life.

precisely the state variables arising in the deterministic problem being solved.[12] It also overcomes the curse of dimensionality in two key ways. First, since the survivor-specific paths of retirement account contributions, account balances, and withdrawals are pre-determined.[13] Thus, although TFA's problem involves hundreds of thousands of state variables, many their values are known ex-ante. Second, the life insurance routine is structured to generate the identical living standard path along all survivor paths as that generated in the consumption-smoothing routine.

4.2 Confirming TFA's Solutions

Although TFA's internal workings are complex, its combination of iterative dynamic programming and grid shrinking permit highly precise solutions within seconds. TFA's solutions can be confirmed in six ways. First, the present-value lifetime budget constraint of each household is satisfied to many decimal places along all survival paths. These conditions 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 (discretionary spending per effective adult) is smoothed (takes the same value) to the 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 in the year before a borrowing constraint is lifted (via, for example, termination of mortgage payments) are zero. 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. 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.[14] In this paper, we assume a maximum (additional) indebtedness of \$0 for all SCF households.

5 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.[15] These data include detailed information on household labor and asset income, assets

[12]This is critically important given that borrowing constraints introduce kinks in the discretionary spending functions and interpolation over kinked functions propagates backwards.

[13]Recall, TFA solves a deterministic problem in which real returns are preset based on assumed nominal returns and an assumed inflation rate.

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

[15]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. See 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

and liabilities, and demographic characteristics.[16]

Running TFA requires additional information not provided by the SCF. First, it needs state identifiers to calculate state-specific taxes and transfer payments. The public-use SCF release does not provide state identifiers, so we allocate SCF households to different states based on the 2016 American Community Survey.[17] Second, TFA needs future earnings to calculate resources along survival paths and past and future covered earnings to calculate Social Security benefits. Here 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 too optimistic. Therefore, 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 welfare program take-up. We use the TFA to directly calculate eligibility and combine SCF data with data from the Annual Social and Economic Supplement (ASEC) to the CPS to infer household- and program-specific take-up. Finally, TFA requires a measure of the pre-tax rate of return on national wealth for our savings and lifetime wealth calculations. The following subsections detail our benchmarking process and methods for these four imputations.

5.1 Benchmarking the 2019 SCF to National Aggregates

SCF 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 the approach outlined in Appendix A and B in Dettling et al. (2015), which benchmarks the 2016 SCF based on "conceptually equivalent" values. Specifically, we set SCF benchmark factors to ensure that SCF-weighted aggregates coincide with conceptually comparable 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 2 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.[18]

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 net worth distribution with only 5.7 percent of these households coming from the list sample.

[16] 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.

[17] Although the non public-use SCF dataset includes state identifiers, its household weights are national i.e., not state-specific. They are, therefore, are of no value for our purposes of appropriately allocating SCF households by state.

[18] 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.

Table 2: SCF Benchmarking Adjustments and Targets

	SCF Unadjusted	Benchmarking Coefficient	SCF Adjusted	Target	% Diff
Wages	7,382[19]	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

5.2 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 American Community Survey (ACS). Having done so, we calculate the distribution across states of ACS households with specific cell characteristics. Next, we assign each SCF household to each of the 51 states (including Washington D.C.) 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.[20] 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).

5.3 Earnings Imputations

To impute 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.[21] 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

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

[20] 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.

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

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, $\hat{y}_{i,j}^a$,

$$\hat{y}_{i,j}^a = \bar{y}_i^a + (a\sigma_p^2/(a\sigma_p^2 + \sigma_e^2))(y_{i,j}^a - \bar{y}_i^a) = (a\sigma_p^2/(a\sigma_p^2 + \sigma_e^2))y_{i,j}^a + (\sigma_e^2/(a\sigma_p^2 + \sigma_e^2))\bar{y}_i^a \qquad (11)$$

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

$$\hat{y}_{i,j}^a = (a/(a+1))y_{i,j}^a + (1/(a+1))\bar{y}_i^a \qquad (12)$$

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

$$\bar{y}_i^{(a-t)} + ((a-t)/a)(\hat{y}_{i,j}^a - \bar{y}_i^a)(\bar{y}_i^{(a-t)}/\bar{y}_i^a) = (t/a)\bar{y}_i^{(a-t)} + ((a-t)/a)\hat{y}_{i,j}^a(\bar{y}_i^{(a-t)}/\bar{y}_i^a) \qquad (13)$$

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.

5.4 Using the American Community Survey to Impute Retirement Probabilities

As discussed in Altig et al. (2022), the SCF respondents are asked about their expected ages of retirement. Not all respond and those that do appear to be overly optimistic.[22] 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

[22] 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 .

26 weeks in the previous year and works less than 21 hours a week this year.[23] 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 cohorts 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.[24]

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

Figure 1 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 1: Fraction of Respondents Working More than 20 Hours Per Week, ACS 2000-2020

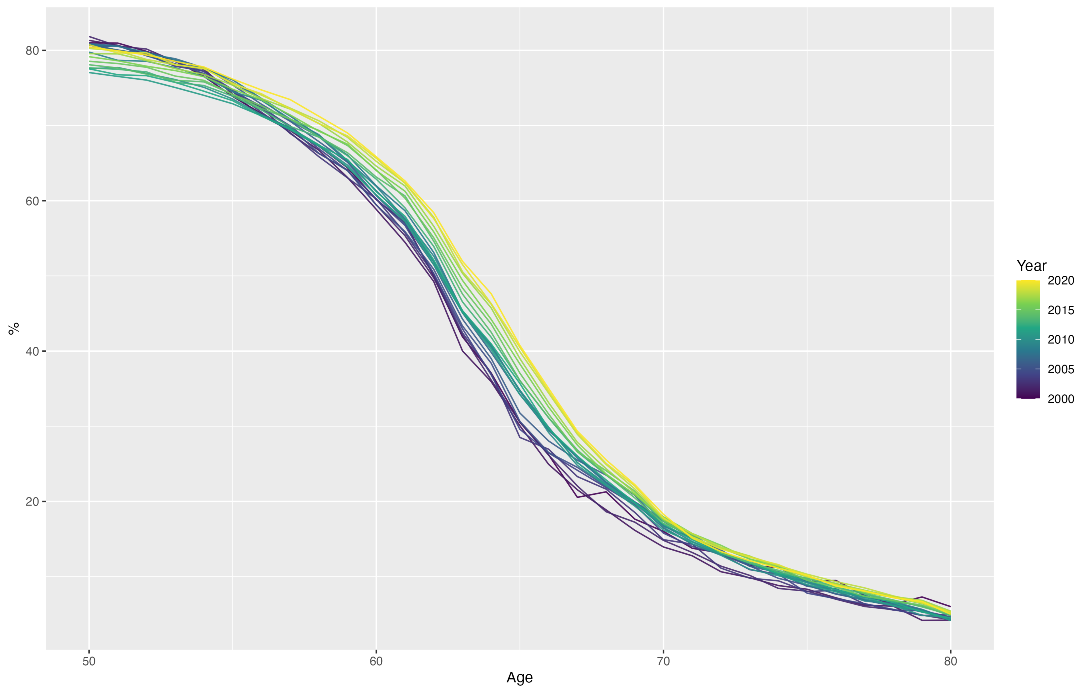


Table 3 shows projected average retirement ages for workers age 50 in 2020 and 2040, re-

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

[24]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 3 and 4.

spectively. 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 3: 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 4 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 4: 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

5.5 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 5. 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.

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 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. 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 5: 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 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 6 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 6: 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

5.6 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 that the share of proprietorship and partnership income comprising labor earnings equals the share of national labor income to national income.[25] 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.

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

5.7 Survival-Path Probabilities

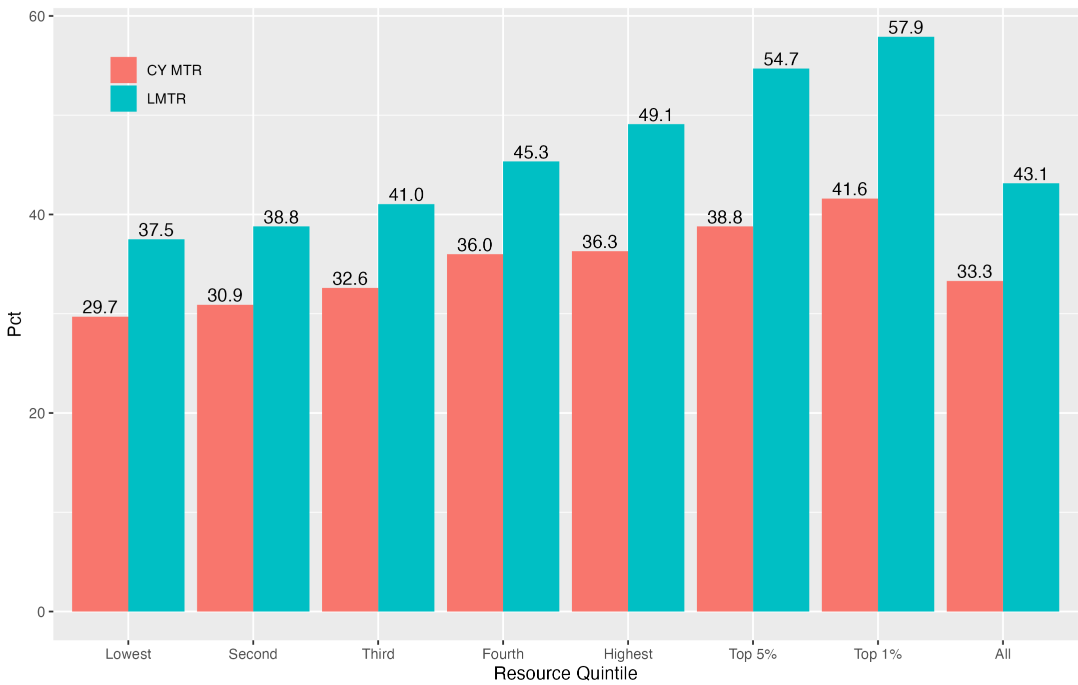
As discussed in Auerbach et al. (2023), Our survival-path probabilities are constructed from underlying mortality rates estimated by the Committee on the Long-Run Macroeconomic Effects of the Aging US Population (2015). This study sorts Health and Retirement Study (HRS) respondents between 1992 and 2010 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. We follow the same procedure, except we sort SCF respondents based on average wage-indexed earnings from age 25 through age 60.

6 Results

6.1 Aggregate Results

Figure 2 shows median marginal tax rates for all age groups, ages 20-69, by lifetime resource quintile. Both measures are calculated based on a \$1,000 increase in current-year earnings. For the overall population, median values of LMTR are 9.8 percentage points higher than median values of CMTR – 43.1 percent versus 33.3 percent. This revealed impact of double taxation is particularly striking for the top 1 percent. For this group, median LMTR is 57.9 percent – considerably higher than its corresponding median CMTR of 41.6 percent. The bottom quintile's median LMTR is 37.5 percent compared with their median CMTR of 29.7 percent.

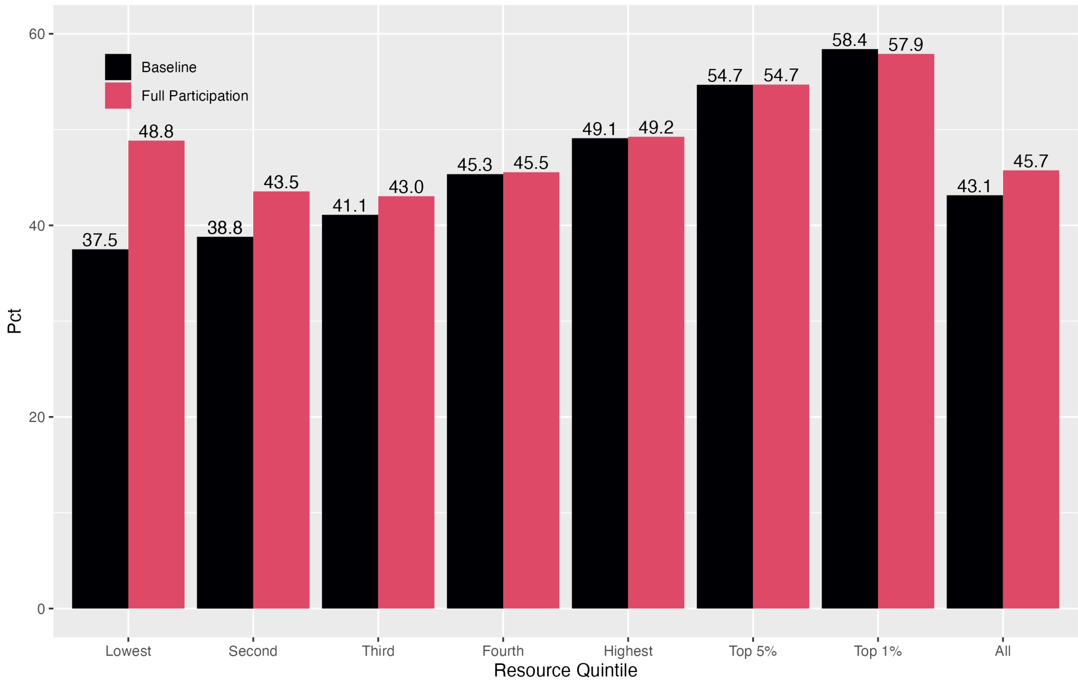
Figure 2: Median Lifetime and Current-Year MTR, Ages 20-69



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 3 shows. For the bottom quintile, the median LMTR would be 48.8 percent, rather than 37.5 percent. As shown in figure A1, 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 quintiles.

Figure 3: Median Lifetime MTR By Welfare Participation Assumption, Ages 20-69



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

6.2 Median Marginal Tax Rates by Age-Resource Quintiles

Figures A2 - A6 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.

6.3 Distribution of Lifetime Marginal Net Tax Rates

Figures 4 and A7 plot distributions of LMTR and CMTR, respectively. There is major dispersion in work disincentives at all resource levels. But whether one considers LMTR or CMTR, the dispersion is dramatic at the bottom of the resource distribution. As shown in table 7, 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.

Figure 4: LMTR from $1,000 Earnings Increase in Current Year, Ages 20-69

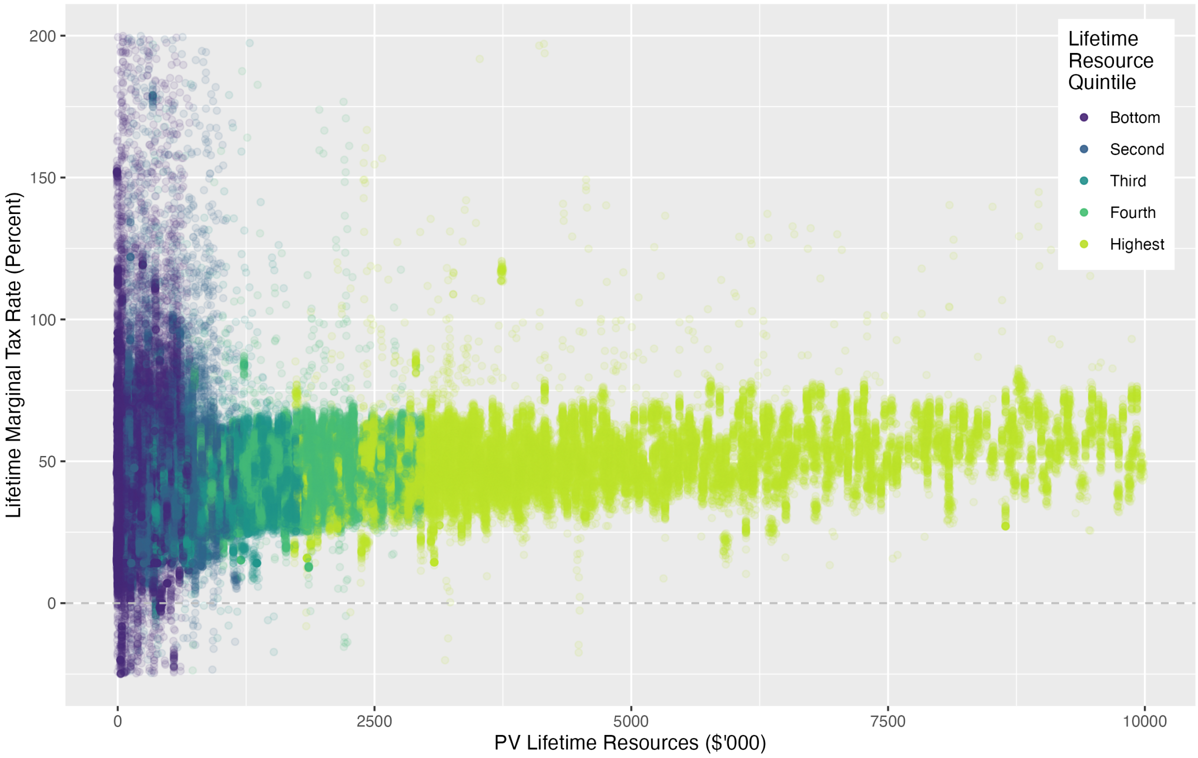


Table 7: Summary Statistics for Marginal Tax Rates, Age 20-69, Imputed Participation

Lifetime Marginal Tax Rates

Resource Group	min	q25	median	mean	q75	q90	max	std.dev
Bottom	-36,035.4	25.3	37.5	43.3	49.7	69.8	20,722.6	439.5
Second	-8,306.1	32.7	38.8	44.0	46.8	54.9	2,649.9	106.1
Third	-2,693.4	34.2	41.0	41.4	48.5	54.7	2,078.9	33.2
Fourth	-55.8	40.1	45.3	46.1	52.4	57.9	801.3	10.7
Highest	-3,010.9	42.8	49.1	50.2	57.2	64.2	657.9	17.0
Top 5%	-3,010.9	46.7	54.7	54.2	61.7	67.5	657.9	20.3
Top 1%	-704.4	49.9	57.9	55.8	65.0	69.8	657.9	13.9
All	-36,035.4	34.9	43.1	45.0	51.5	59.7	20,722.6	185.5

Current-Year Marginal Tax Rates

Resource Group	min	q25	median	mean	q75	q90	max	std.dev
Bottom	-2,821.1	22.4	29.7	35.6	40.4	58.8	3,365.5	104.0
Second	-1,706.0	28.0	30.9	40.0	38.0	44.5	1,681.1	67.2
Third	-2,054.6	29.2	32.6	33.5	37.9	40.5	1,006.1	18.1
Fourth	-18.6	31.0	36.0	35.3	39.6	41.8	1,471.2	11.2
Highest	-8.0	30.0	36.3	35.8	40.9	44.3	203.5	8.6
Top 5%	-8.0	33.6	38.8	38.4	43.1	47.8	185.5	8.4
Top 1%	-8.0	37.3	41.6	40.8	45.2	50.1	136.2	8.7
All	-2,821.1	28.4	33.3	36.0	39.4	43.6	3,365.5	51.2

Figures A8, A9, and table A1 repeat figure 4, figure A7 and table 7, 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 A8 and 15 percent of CMTR values in figure A9 values exceed 75 percent.[26] 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 would surely 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 induced less work, lower labor earnings, and, on balance, increase poverty.

Consider next figure 5 that 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.

Figure 5: Current-Year vs Lifetime Marginal Tax Rates from $1,000 Earnings Increase in Current Year, Ages 20-69

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

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. As we show in section 6.5.3, in certain exceptional cases, current-year benefit losses may result in a combination of positive CMTR and negative LMTR.

Figures 4, A7, and 5, in conjunction, also convey a critical message. Contrary to the predictions 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 9.

Consider the bottom quintile of 20-29 year olds in table A2. This group's median LMTR is 35.7 percent. The 25th and 75th percentile values are 21.3 percent and 53.0 percent, for a spread of 31.7 percentage points, which is almost as large as the median rate. The group's minimum LMTR is -2,500.4 percent; its maximum rate is 20,722.6 percent; and its standard deviation is 374.4 percentage points. Compare this group's tremendous LMTR dispersion with that of the top quintile of 50-59 year olds, as shown in table A5. For this set of households, the median LMTR is 52.2 percent, the 25th percentile value is 45.6 percent, and the 75th percentile value is 59.7 percent. Hence, the 25th-75th percentile difference is only 14.1 percentage points compared with 31.7 percentage points for the poorest 20-29 year-olds.

The LMTR dispersion between minimum and maximum values is far more dramatic. Across all households and under our baseline imputed welfare participation assumption, the maximum LMTR is 20,722.6 percent and the minimum is -36,035.4 percent. The household with the maximum rate experiences a $207,226 increase in net taxes as a result of earning an extra $1,000. The household with the minimum rate experiences a $360,354 increase in net benefits from earning another $1,000.

The potential poverty trap arising under our fiscal system is highlighted by the 75th LMTR-percentile values for the bottom quintiles. As shown in tables A2 to A6, moving from the youngest to the oldest cohorts, these values are 53.0 percent, 51.9 percent, 50.4 percent, 46.0 percent, and 46.8 percent. Hence, one in four of our poorest households, regardless of age, make roughly as much for the government as for themselves in earning an extra $1,000. The precise degree to which disincentives of this magnitude discourage work remains an open question.

With some exceptions, 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. With some exceptions, most households eligible for income- and asset-tested benefit programs are among the first and second resource quintiles.

While 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 more, 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, 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.

6.4 Decomposing Average Marginal Net Tax Rates

Table 8 shows the sources of mean lifetime and current-year marginal tax rates for one particular group, the lowest resource quintile of 20-69 year-olds. 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 8: Breakdown of LMTR and CMTR sources, Lowest Resource Quintile

	CY Baseline	CY Marginal	CY Diff	PV Baseline	PV Marginal	PV Diff
Federal Income Tax	1,130	1,250	121	19,103	19,239	137
State Income Tax	202	214	11	2,984	3,001	16
Other Taxes	1,538	1,610	72	29,132	29,227	95
Total Taxes	2,870	3,074	204	51,219	51,467	248
SNAP	1,145	1,105	-40	9,959	9,893	-66
TANF	40	39	-1	72	71	-1
Section 8	409	397	-11	4,426	4,413	-12
CCDF	470	463	-7	1,948	1,940	-8
Social Security	5,388	5,386	-1	100,130	100,145	15
SSI	2,315	2,268	-47	25,319	25,196	-123
Other Transfers	9,129	9,118	-10	136,799	136,735	-63
Total Transfer Payments	18,895	18,776	-119	278,652	278,394	-258
Net Taxes	**-16,025**	**-15,702**	**323**	**-227,433**	**-226,927**	**506**

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

Table 8 shows that, for households in the bottom quintile, their 32.3 percent average CMTR arises from an average reduction of transfer payments of $119 and increase in taxes of $204 for $1,000 in additional current earnings. The corresponding present-value reduction in lifetime benefits is much larger at $258. The increase in lifetime taxes is $248. $66 of the present-value reduction in benefits can be attributed to loss of SNAP benefits, and $123 to loss of SSI.

6.5 Understanding Very High and Very Low Lifetime Marginal Tax Rates

We present, in this subsection, details of three SCF households with very high or very low lifetime marginal tax rates. Case I describes a high earner with a much higher LMTR than his 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 their CMTR is positive.

6.5.1 Case I

This case study helps clarify why LMTRs can be so large, both in general as well as relative to CMTRs. The 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 9, 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, due to extra taxes on consumption (Arizona's sales tax rate is 7.9 percent) and extra saving, i.e., double taxation arising from federal and state income taxes paid beyond the current year.

Table 9: Breakdown of LMTR and CMTR sources, Case I in Arizona

	CY Baseline	CY Marginal	CY Diff	PV Baseline	PV Marginal	PV 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**

Specifically, 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 of state income tax amounts to $17, and other taxes – primarily the state sales tax – add an additional $64.

6.5.2 Case II

This case involves an Idaho couple, both age 37 and both high-school educated, with three children ages six, six, and ten. The couple's limited resources place them in the bottom resource quintile. Their LMTR is 652.9 percent, which arises primarily as a result of losing SNAP benefits from earning an extra $1,000. Idaho has three eligibility tests for SNAP: the gross income, net income, and asset tests. 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 $5,000.[27] Clearly, earning even a bit too much money can come at the loss of all SNAP benefits. And those benefits can be considerable: in 2023, the maximum monthly SNAP allotment for the family of five was $1,116.[28]

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

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

Table 10: Breakdown of LMTR and CMTR sources, Case II

	CY Baseline	CY Marginal	CY Diff	PV Baseline	PV Marginal	PV 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**

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 of Section 8 housing assistance and CCDF. Participating in these programs significantly reduces available SNAP benefits and, thus, the size of the potential loss of these benefits from additional income. To be clear, the couple's 652.9 percent marginal tax under partial participation arises from the loss of other benefits besides SNAP.

6.5.3 Case III

This case illustrates the potential for negative LMTRs to coincide with positive CMTRs. It features a bottom-resource quintile Ohio couple, ages 40 and 42. The couple's CMTR is 36.9 percent, produced by an increase in taxes of 14.6 cents per dollar of extra earnings, and a loss in SNAP benefits of 22.3 cents per dollar. 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 makes them eligible for more SSI benefits – $80 to $200 more per year – for every year after they retire. As table 11 shows, the net present value decrease in lifetime net taxes due to increase SSI benefits is $3,360.

Table 11: Breakdown of LMTR and CMTR sources, Case III

	CY Baseline	CY Marginal	CY Diff	PV Baseline	PV Marginal	PV 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**

7 The Cost of Labor Force Entry

In this section, we consider work-participation taxation for the subset of SCF respondents who report they are neither working, disabled, collecting Social Security, nor older than their imputed retirement age. Rather that 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. 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 roughly $15 per hour. We estimate CMTRs and LMTRs based on this amount.

Figure 6 summarizes. Across all households in our sub-sample, the median full-time work-participation tax LMTR is 45.0 percent. The part-time work-participation tax has a median LMTR of 40.6 percent. For the bottom quintile, going back to full-time work entails a higher LMTR of 46.7 percent and a CMTR that is also very high, at 44 percent. Part-time participation is taxed at a lower rate, although the median CMTR is still 34.8 percent and the LMTR is an impressive 38.2 percent.

Tables 12 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 CY 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.

Figure 6: Median LMTR and CMTR From Labor Force Entry, Pre-Retirement Age and Non-working SCF Households

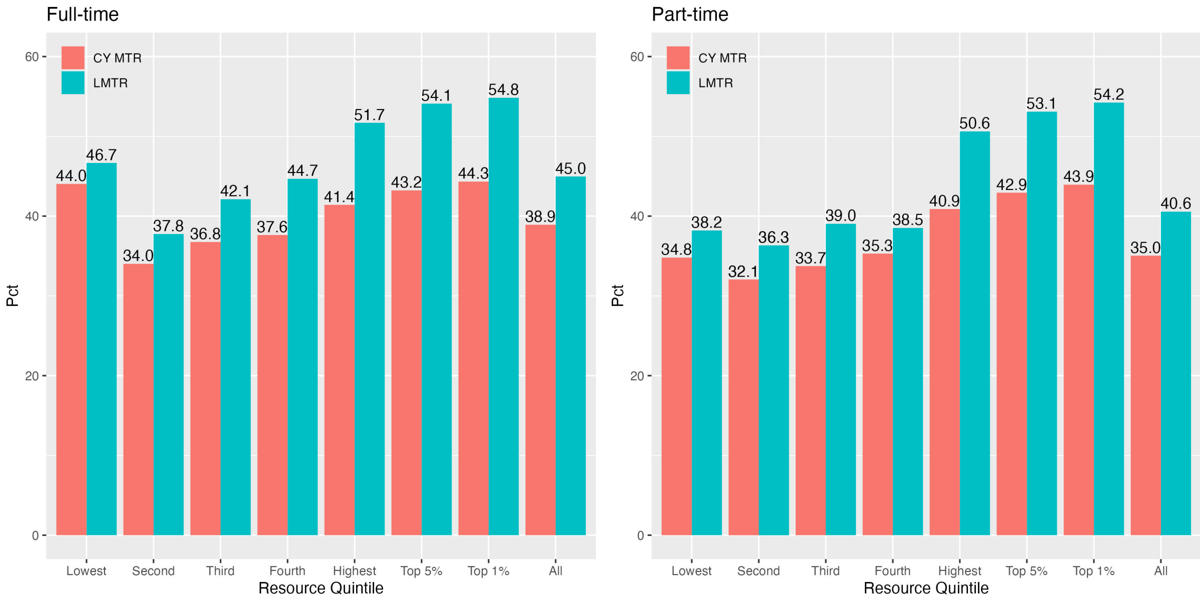


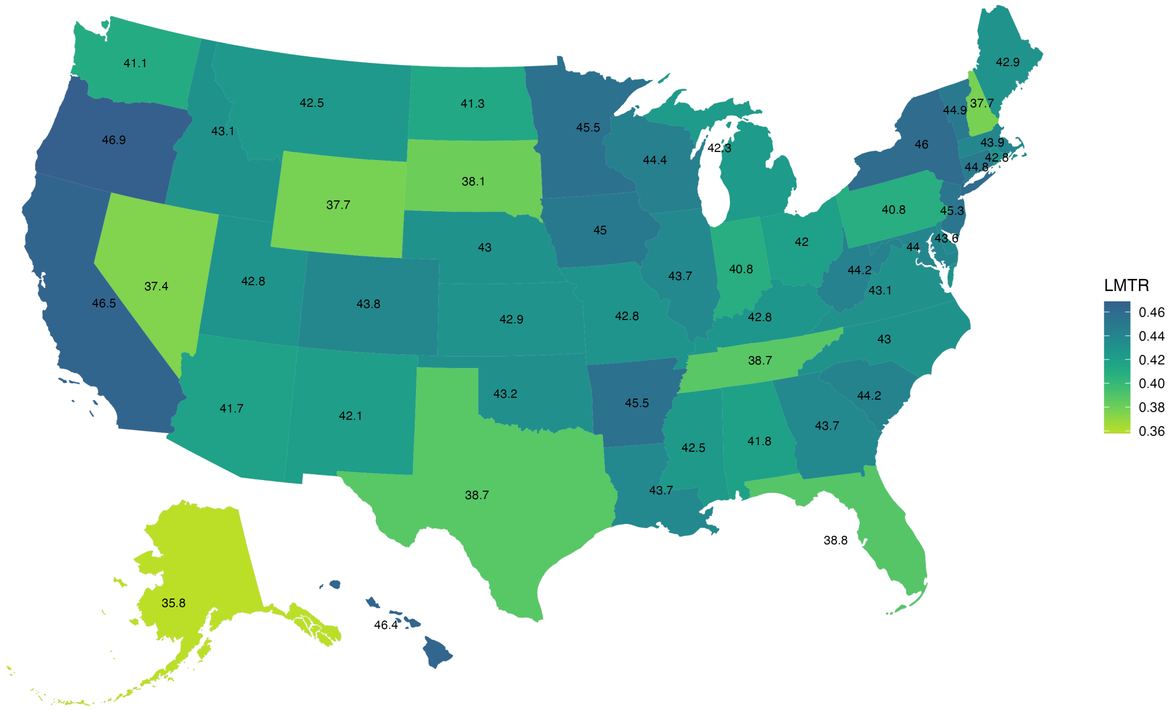
Table 12: Breakdown of LMTR and CMTR sources from Full-time Labor Force Entry, Pre-Retirement Age, Bottom Resource Quintile, Non-working SCF Households

	CY Baseline	CY Marg.	CY Diff	PV Baseline	PV Marg.	PV 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

8 Cross-State Variation

This section describes the variation in lifetime marginal tax rates across U.S. states. 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 7 shows the cross-state variation in median lifetime marginal tax rates. Figure A10 in the Appendix provides similar information for the current-year marginal tax rates.

Figure 7: Cross-State Variation in Median LMTRs (Age 30-39, Lowest Resource Quintile)



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

Figure 7 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 13 reports this measure for households for different resource quintiles.

Table 13 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 marginal tax rate 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

Table 13: 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

rates.[29]

9 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.

$$DWL \approx -\Big(t\Delta x + \frac{1}{2}\Delta t \Delta x\Big). \tag{14}$$

The first term in (14) 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 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

$$\Big(\frac{dx}{dp}\frac{p}{x}\Big)\sum_i \frac{t_i}{p_i}x_i\Delta t_i. \tag{15}$$

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 (15) is non-

[29] 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.

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 (15) becomes

$$\frac{t}{p}\Big(\frac{dx}{dp}\frac{p}{x}\Big)\sum_i x_i \Delta t_i \tag{15*}$$

which equals 0 by the assumption that the static revenue remains unchanged. Then, equation (14) simplifies to $-\frac{1}{2}\sum_i \Delta t_i \Delta x_i$, which we approximate by

$$\begin{aligned} -\frac{1}{2}\sum_i \Delta t_i \frac{dx}{dp}(-\Delta t_i) &= \frac{1}{2}\sum_i \Big(\frac{dx}{dp}\frac{p}{x}\Big) p_i x_i \Big(\frac{\Delta t_i}{p_i}\Big)^2 \\ &= \frac{1}{2}\Big(\frac{dx}{dp}\frac{p}{x}\Big)\sum_i p_i x_i \Big(\frac{\Delta t_i}{p}\Big)^2. \end{aligned} \tag{16}$$

Expressing DWL as a faction of cohort net income, $D = \sum_i p_i x_i$, (16) becomes

$$\frac{1}{2}\Big(\frac{dx}{dp}\frac{p}{x}\Big)\sum_i \frac{p_i x_i}{D}\Big(\frac{\Delta t_i}{p}\Big)^2. \tag{16*}$$

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, (16) can be rewritten as:

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

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.[30] 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 (17) to

$$\frac{1}{2}\Big(\frac{dx}{dp}\frac{p}{x}\Big)\frac{1}{N}\sum_i \left(\Big(\frac{\Delta t_i}{p}\Big)^2 - \Big(\sum_i \frac{\Delta t_i}{p}\Big)^2\right) = \frac{1}{2}\Big(\frac{dx}{dp}\frac{p}{x}\Big) wvar\Big(\frac{\Delta t_i}{p}\Big), \tag{17*}$$

where the variance accounts for either our imputed household weights or each household's weighted observed labor income share of the cohort.[31] 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.

[30] 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.

[31] 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.

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. [32] 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,

$$\frac{\Delta t_i}{p} = \frac{\theta_i - \bar{\theta}}{1-\bar{\theta}} \tag{18}$$

We estimate DWL for two scenarios, assuming, respectively, realistic and full welfare-program participation.[33] Results are presented in tables 14 and 15. 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 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 14: 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 15: 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 14 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

[32] 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.

[33] 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%.

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 15. 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.

10 Conclusion

This paper 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, over each household's 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) or permanent (through retirement) 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).

Our SCF data are benchmarked to national aggregates. In addition, we carefully impute earnings, retirement ages, state residence, survival probabilities, and benefit-program participation using a range of national databases. But perhaps the hallmark of our study is its intense attention to fiscal detail. The paper incorporates, in considerable detail, every major federal and state tax and benefit program. For example, we incorporate the precise provisions of 51 distinct Medicaid programs corresponding to the 51 separate Medicaid programs in the 50 states plus Washington, D.C.

Our findings are striking. Even accounting for partial benefit program take up, American households typically face very high marginal lifetime net tax rates. Among all households headed by respondents age 20-69, the median tax rate 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. Assuming partial benefit program take up, marginal net tax rates do not form a U-shaped pattern with respect to resource level. Instead, they steadily rise. However, were all Americans to participate in all benefit programs for which they are eligible, the marginal tax-rate versus resources pattern would, indeed, be U-shaped. Future tax consequences also matter. The median LMTR across our entire sample of 43.1 percent is close to one-third higher than the corresponding current-year marginal rate of 33.3 percent.

These findings are important. Tax hikes or increases in benefit claw-back provisions could confront typical U.S. workers with marginal tax rates above 50 percent. But one of our most important findings involves heterogeneity. 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, respectively, with minimum and maximum rates of -14,984 percent and 18,449 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, a forensic analysis of U.S. work incentives that fully accounts for all major federal and state fiscal policy reveals major work disincentives, a significant poverty lock, huge horizontal differences in work disincentives 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.

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Appendix

Figure A1: Median Current-Year MTR By Welfare Program Participation Assumption, Ages 20-69

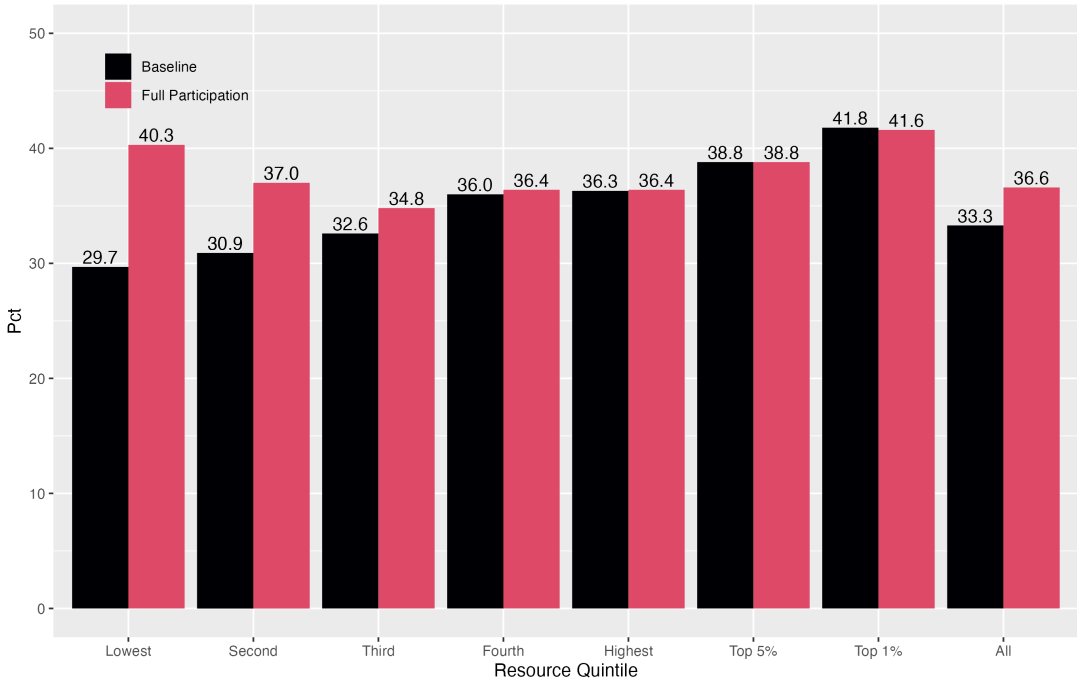


Figure A2: Median Lifetime and Current-Year MTR, Ages 20-29

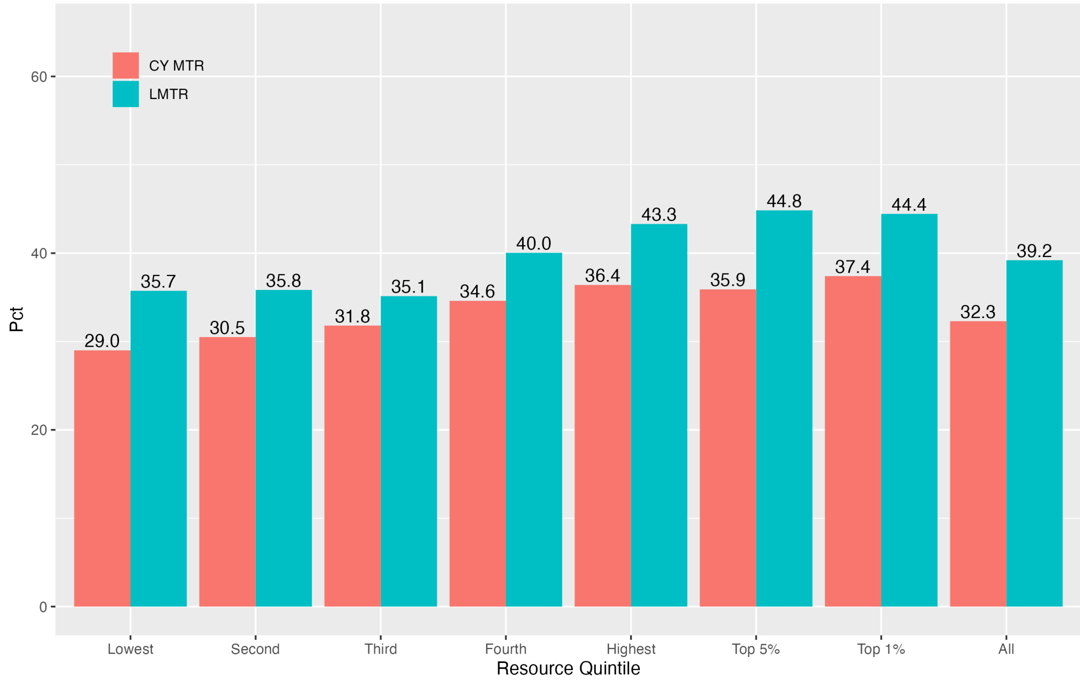


Figure A3: Median Lifetime and Current-Year MTR, Ages 30-39

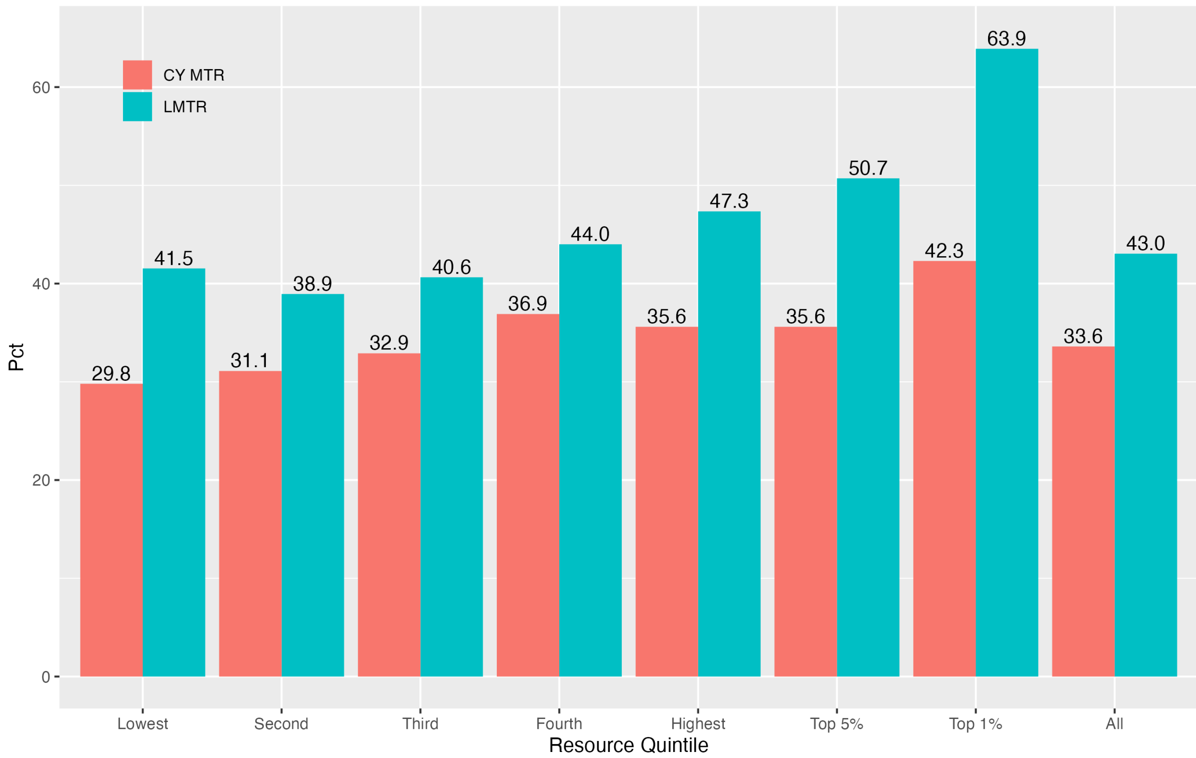


Figure A4: Median Lifetime and Current-Year MTR, Ages 40-49

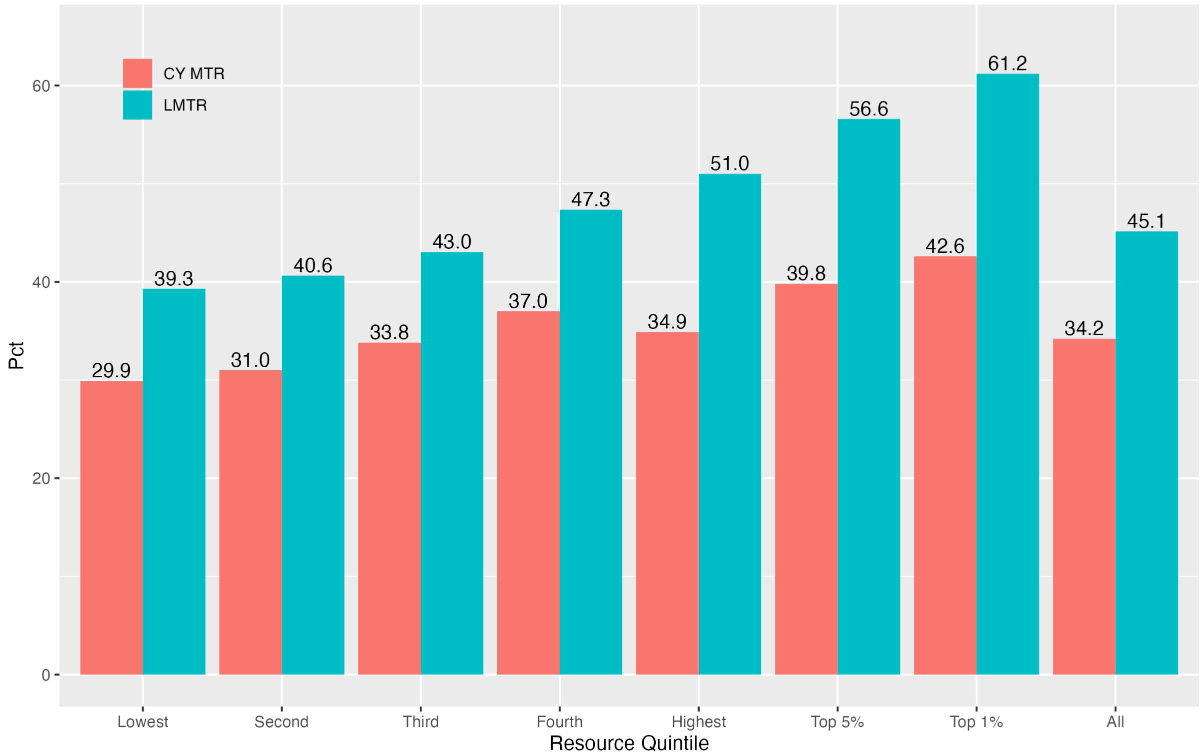


Figure A5: Median Lifetime and Current-Year MTR, Ages 50-59

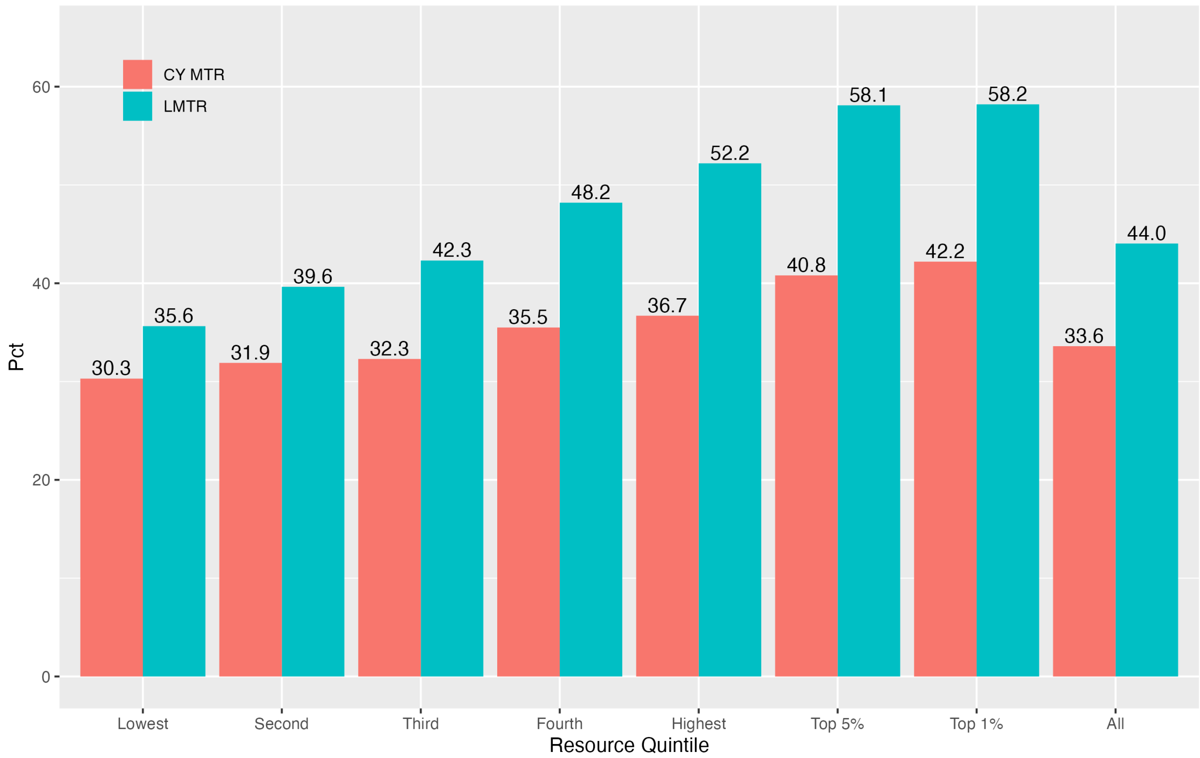


Figure A6: Median Lifetime and Current-Year MTR, Ages 60-69

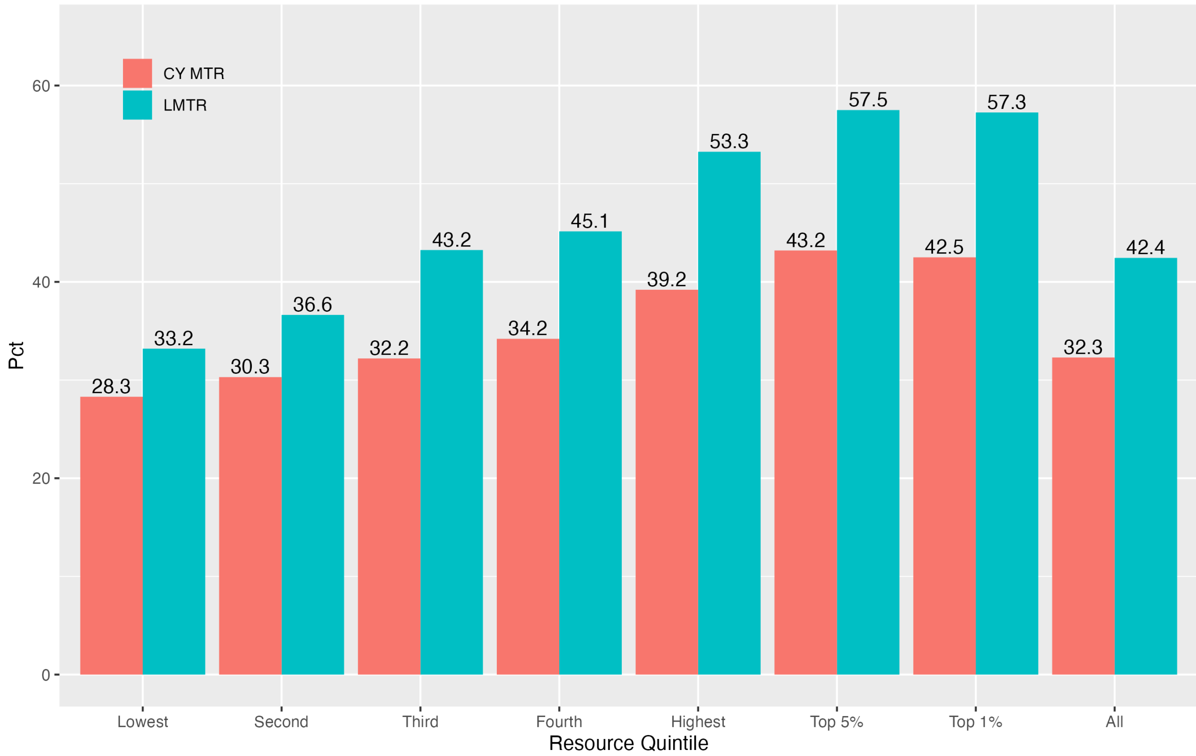


Figure A7: Current-Year Marginal Tax Rates from $1,000 Earnings Increase in Current Year, Ages 20-69

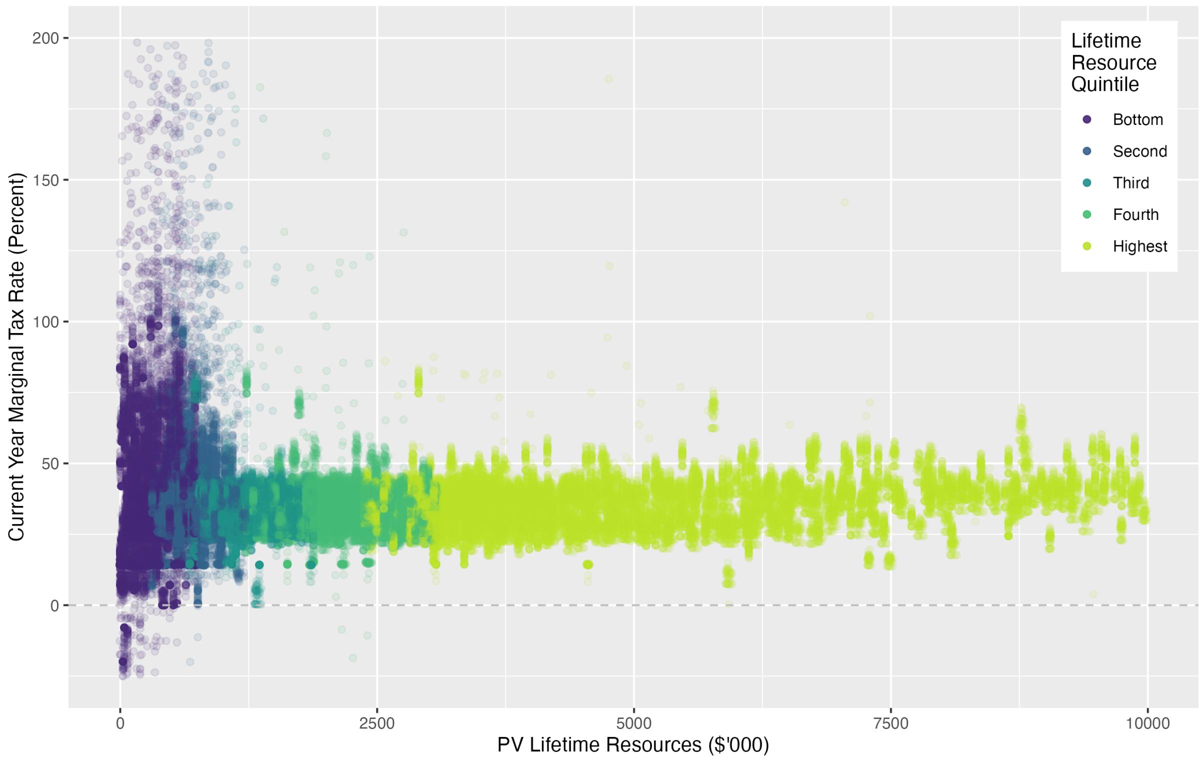


Figure A8: Lifetime Marginal Tax Rates from $1,000 Earnings Increase in Current Year, Ages 20-69, Full Welfare Participation

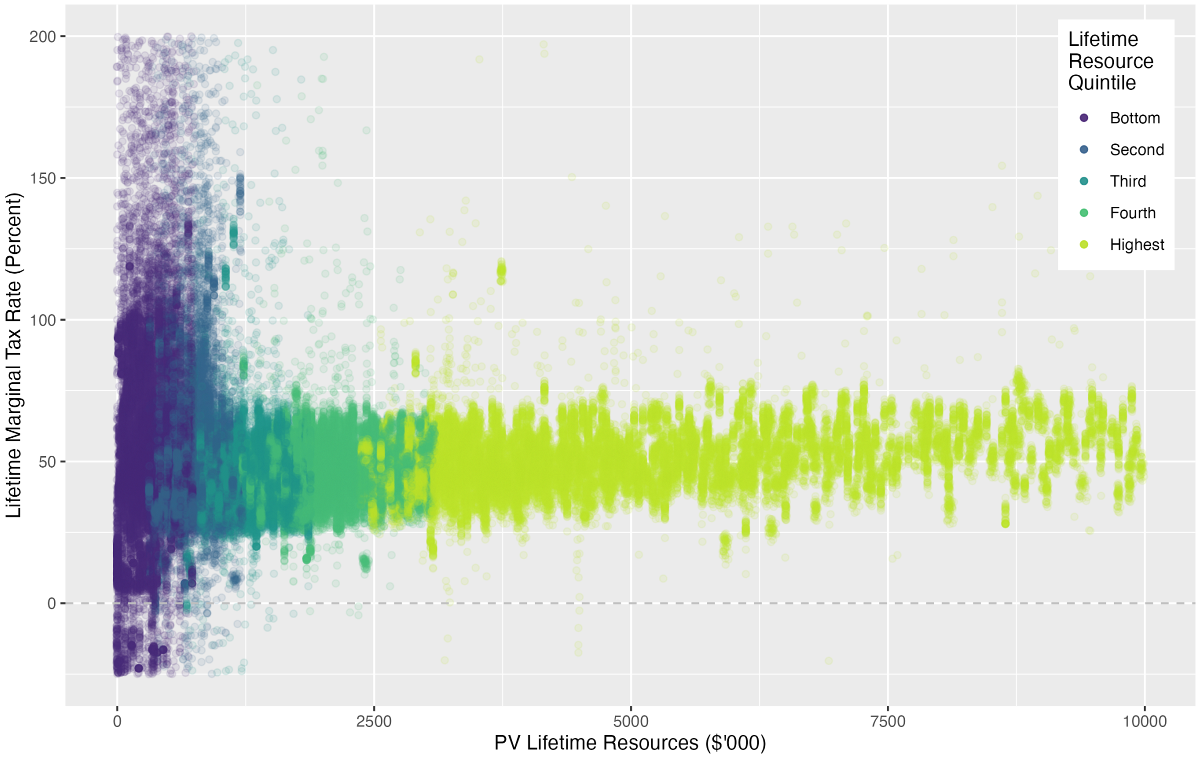


Figure A9: Current-Year Marginal Tax Rates from $1,000 Earnings Increase in Current Year, Ages 20-69, Full Welfare Participation

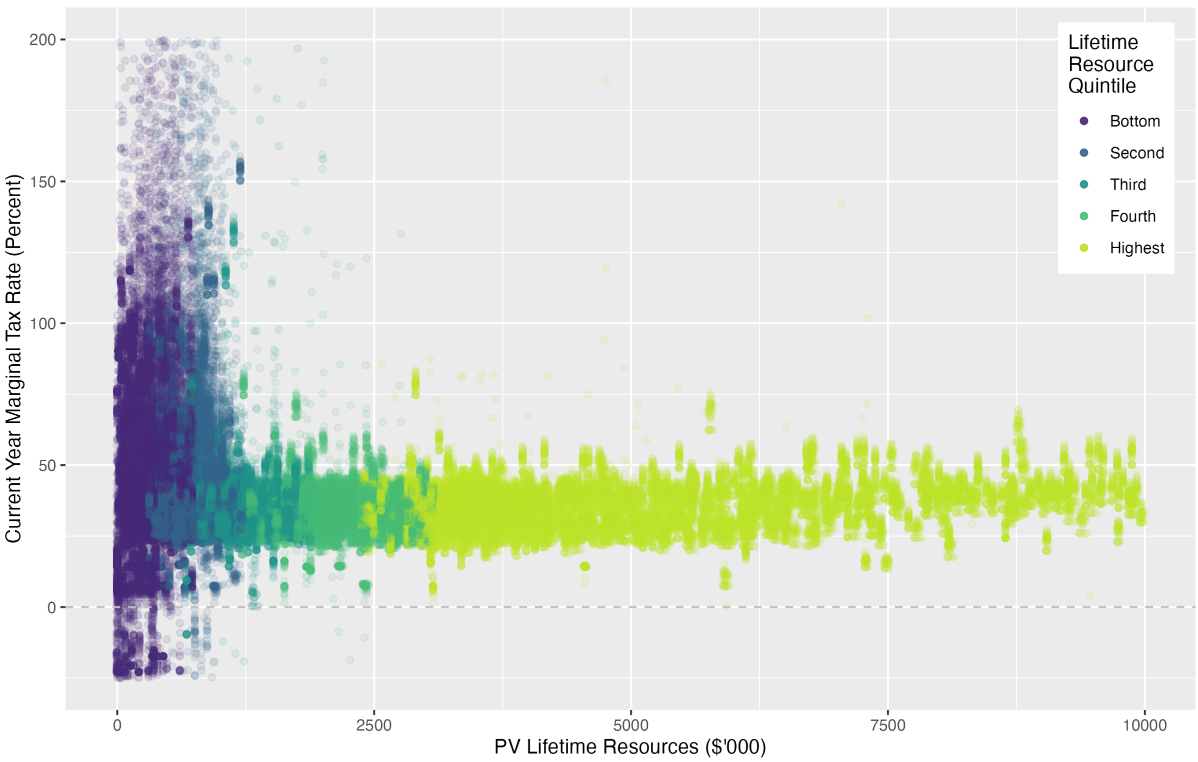
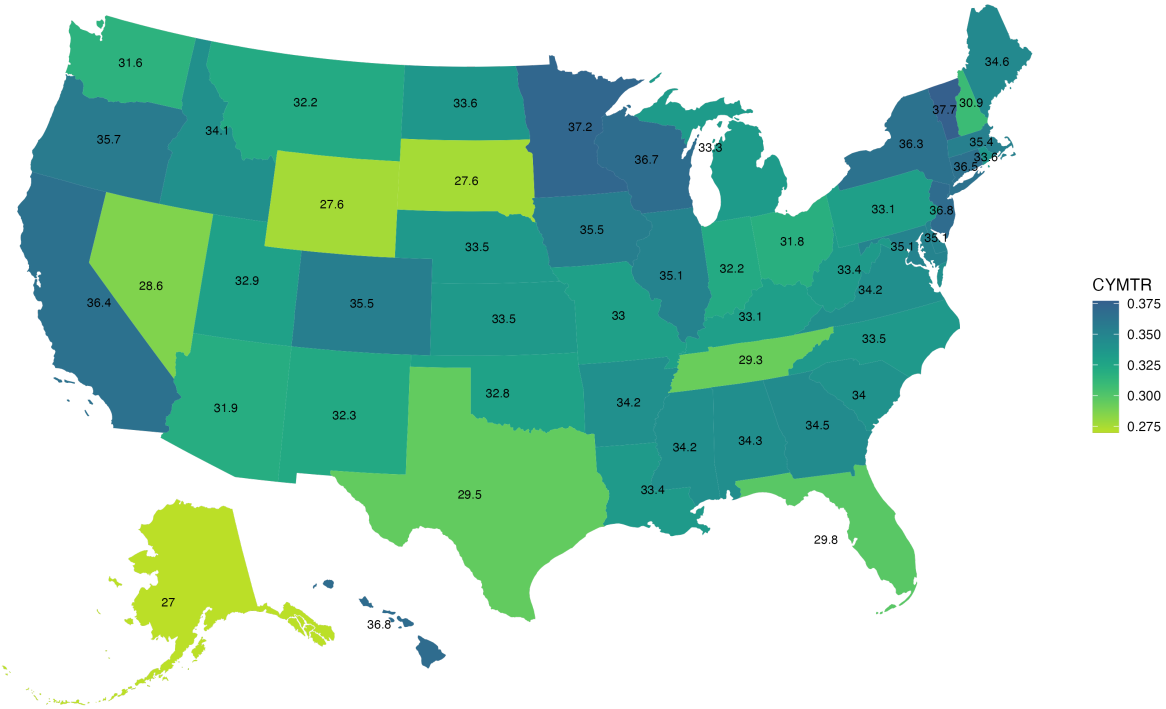


Figure A10: Cross-State Variation in Median CMTRs (Age 30-39, Lowest Resource Quintile)



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

Figure A11: Difference Between Highest and Lowest State LMTR from $1,000 Earnings in Current Year, Ages 20-69

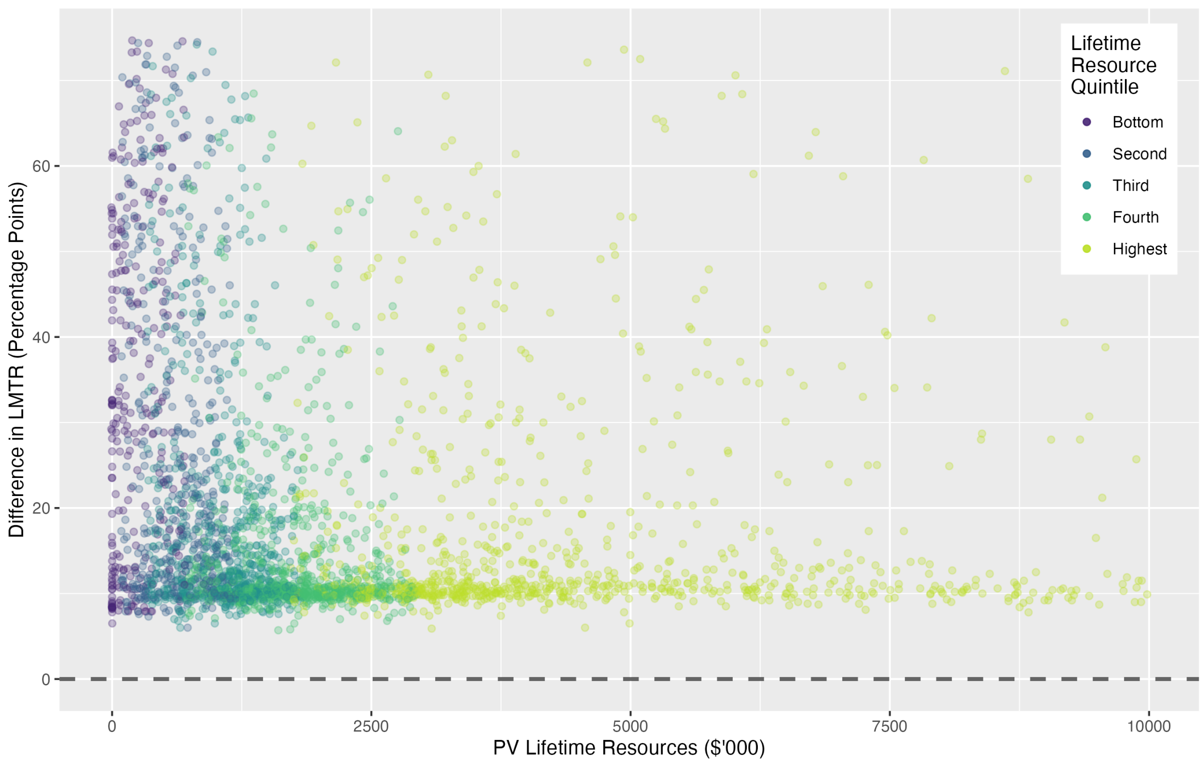


Table A1: Summary Statistics for Marginal Tax Rates, Age 20-69, Full Participation

Lifetime Marginal Tax Rates

Resource Group	min	q25	median	mean	q75	q90	max	std.dev
Bottom	-20,247.1	34.8	48.8	55.2	68.7	99.2	22,933.2	636.1
Second	-20,223.2	35.7	43.5	52.1	53.6	72.4	15,411.0	282.8
Third	-3,066.9	36.1	43.0	50.5	49.9	56.4	9,087.5	119.8
Fourth	-3,017.8	40.4	45.5	46.2	52.7	58.3	3,595.7	49.4
Highest	-3,010.9	42.9	49.2	50.2	57.2	64.2	1,252.0	18.3
Top 5%	-3,010.9	46.6	54.7	54.1	61.7	67.5	1,252.0	21.3
Top 1%	-704.4	50.1	57.9	55.8	65.0	69.7	1,252.0	16.5
All	-20,247.1	38.6	45.7	50.8	55.0	66.4	22,933.2	288.3

Current-Year Marginal Tax Rates

Resource Group	min	q25	median	mean	q75	q90	max	std.dev
Bottom	-3,158.8	28.7	40.3	42.0	57.9	86.7	4,270.9	145.3
Second	-2,704.4	30.0	37.0	45.1	42.9	66.3	3,911.9	142.1
Third	-2,054.6	29.9	34.8	38.4	39.3	42.0	3,487.1	84.6
Fourth	-407.6	31.3	36.4	35.7	39.7	42.0	1,553.4	14.5
Highest	-156.2	30.1	36.4	35.9	41.0	44.6	280.3	8.7
Top 5%	-8.0	33.6	38.8	38.4	43.1	47.8	185.5	8.4
Top 1%	-8.0	37.3	41.6	40.8	45.2	50.1	136.2	8.7
All	-3,158.8	30.1	36.6	39.4	41.3	52.9	4,270.9	89.1

Table A2: Summary Statistics for Marginal Tax Rates, Age 20-29

Lifetime Marginal Tax Rates

Resource Group	min	q25	median	mean	q75	q90	max	std.dev
Bottom	-2,500.4	21.3	35.7	62.2	53.0	74.4	20,722.6	374.4
Second	-3,301.1	31.2	35.8	57.8	48.9	64.4	1,795.7	144.5
Third	-602.9	32.2	35.1	39.0	42.1	54.1	559.6	26.6
Fourth	18.7	33.6	40.0	42.5	47.8	61.5	801.3	17.7
Highest	21.6	38.6	43.3	43.6	47.1	56.5	205.5	8.9
Top 5%	21.6	39.8	44.8	46.1	55.3	61.3	70.5	10.8
Top 1%	21.6	26.5	38.5	38.4	43.8	57.0	66.8	13.7
All	-3,301.1	32.2	39.2	49.0	47.4	60.5	20,722.6	191.4

Current-Year Marginal Tax Rates

Resource Group	min	q25	median	mean	q75	q90	max	std.dev
Bottom	-224.7	14.2	29.0	49.6	38.2	58.8	3,365.5	203.7
Second	-216.3	27.5	30.5	54.8	37.2	60.7	1,681.1	127.0
Third	-407.6	28.8	31.8	34.2	36.7	40.5	623.8	25.8
Fourth	8.4	30.3	34.6	34.9	39.9	42.2	1,471.2	26.8
Highest	19.0	31.6	36.4	35.6	40.1	42.3	203.5	6.2
Top 5%	22.2	28.9	35.9	34.4	38.9	41.6	48.1	6.0
Top 1%	24.1	27.9	29.9	33.3	41.4	43.4	48.1	7.2
All	-407.6	28.3	32.3	41.9	39.1	44.1	3,365.5	114.9

Table A3: Summary Statistics for Marginal Tax Rates, Age 30-39

Lifetime Marginal Tax Rates

Resource Group	min	q25	median	mean	q75	q90	max	std.dev
Bottom	-14,983.6	27.2	41.5	36.1	51.9	71.2	18,449.0	475.4
Second	-348.9	32.7	38.9	46.8	48.1	57.0	1,493.6	50.1
Third	-218.2	33.1	40.6	41.2	48.2	56.4	231.3	11.2
Fourth	24.7	40.2	44.0	45.5	50.8	57.8	117.5	8.6
Highest	13.4	41.6	47.3	49.1	56.2	64.1	144.9	11.1
Top 5%	13.4	45.3	50.7	52.6	59.2	66.5	144.9	11.1
Top 1%	36.1	53.0	59.6	59.7	67.5	72.2	144.9	9.3
All	-14,983.6	35.3	43.0	43.7	51.4	60.4	18,449.0	219.2

Current-Year Marginal Tax Rates

Resource Group	min	q25	median	mean	q75	q90	max	std.dev
Bottom	-760.4	23.3	29.8	34.9	42.8	61.7	1,081.7	56.5
Second	0.3	28.3	31.1	40.9	38.6	45.7	1,493.2	52.3
Third	-216.3	29.6	32.9	33.1	37.8	40.6	869.3	12.5
Fourth	19.4	32.4	36.9	35.7	39.7	41.4	131.4	5.5
Highest	18.7	30.4	35.6	35.2	39.8	42.7	185.5	7.4
Top 5%	19.9	30.3	35.6	35.8	40.6	45.0	185.5	8.7
Top 1%	25.9	37.8	41.6	41.5	46.0	49.2	124.4	6.9
All	-760.4	28.8	33.6	36.0	39.3	43.4	1,493.2	35.6

Table A4: Summary Statistics for Marginal Tax Rates, Age 40-49

Lifetime Marginal Tax Rates

Resource Group	min	q25	median	mean	q75	q90	max	std.dev
Bottom	-36,035.4	24.5	39.3	44.2	50.4	69.2	8,172.6	470.9
Second	-8,306.1	33.1	40.6	38.7	49.4	56.5	1,552.9	126.5
Third	-673.0	35.4	43.0	43.7	50.9	56.3	593.1	15.3
Fourth	-2.8	42.8	47.3	47.7	52.8	57.3	115.6	8.1
Highest	-3,010.9	45.3	51.0	51.1	56.4	62.8	238.2	28.2
Top 5%	-3,010.9	51.2	56.6	56.6	62.7	68.1	238.2	38.5
Top 1%	-137.2	54.8	62.0	60.0	67.0	71.0	238.2	10.5
All	-36,035.4	37.2	45.1	45.1	52.8	59.0	8,172.6	207.4

Current-Year Marginal Tax Rates

Resource Group	min	q25	median	mean	q75	q90	max	std.dev
Bottom	-1,638.5	22.5	29.9	32.8	40.6	56.3	1,284.0	45.6
Second	-1,706.0	28.0	31.0	37.0	38.9	43.7	1,584.2	63.3
Third	-41.0	29.5	33.8	34.3	38.5	40.9	1,006.1	14.1
Fourth	-8.6	33.6	37.0	36.0	39.7	42.0	119.1	5.8
Highest	0.3	28.5	34.9	34.7	40.3	43.8	85.9	8.2
Top 5%	3.4	35.7	39.8	39.3	43.1	47.2	85.9	7.4
Top 1%	3.4	38.4	42.6	42.7	47.2	51.5	62.2	7.0
All	-1,706.0	28.4	34.2	35.0	39.5	43.4	1,584.2	33.2

Table A5: Summary Statistics for Marginal Tax Rates, Age 50-59

Lifetime Marginal Tax Rates

Resource Group	min	q25	median	mean	q75	q90	max	std.dev
Bottom	-7,323.1	27.5	35.6	33.8	46.0	60.9	8,607.6	222.0
Second	-345.8	33.8	39.6	43.9	44.9	51.3	1,360.1	47.7
Third	-2,693.4	36.6	42.3	41.0	48.3	52.9	2,078.9	53.6
Fourth	-55.8	42.2	48.2	48.1	54.1	57.9	234.5	9.2
Highest	-704.4	45.6	52.2	53.0	59.7	66.3	218.3	12.2
Top 5%	-704.4	51.3	58.1	57.3	64.7	69.6	157.1	13.3
Top 1%	-704.4	54.6	59.4	58.5	64.3	68.3	129.2	14.9
All	-7,323.1	36.6	44.0	43.9	51.7	59.0	8,607.6	89.1

Current-Year Marginal Tax Rates

Resource Group	min	q25	median	mean	q75	q90	max	std.dev
Bottom	-2,821.1	25.3	30.3	27.1	39.6	51.5	761.7	82.3
Second	-753.3	28.4	31.9	37.5	38.2	41.7	1,451.0	49.1
Third	-36.8	28.8	32.3	32.9	37.9	40.5	201.1	6.5
Fourth	2.9	30.6	35.5	35.2	39.3	42.1	182.6	6.5
Highest	3.5	29.6	36.7	36.1	41.8	45.7	136.2	8.3
Top 5%	3.5	37.1	40.8	40.3	44.3	48.4	136.2	7.7
Top 1%	3.5	38.9	42.5	42.0	45.4	49.8	136.2	8.0
All	-2,821.1	28.6	33.6	33.8	39.3	43.5	1,451.0	36.6

Table A6: Summary Statistics for Marginal Tax Rates, Age 60-69

Lifetime Marginal Tax Rates

Resource Group	min	q25	median	mean	q75	q90	max	std.dev
Bottom	-8,773.0	21.1	33.2	50.2	46.8	73.5	15,654.5	635.4
Second	-2,860.7	31.6	36.6	32.1	43.0	49.1	2,649.9	151.2
Third	-1,716.2	36.0	43.2	41.4	49.0	53.0	604.6	32.9
Fourth	-3.2	39.3	45.1	45.3	51.4	56.3	200.9	11.0
Highest	-95.2	44.1	53.3	53.0	60.6	66.7	657.9	13.5
Top 5%	-95.2	51.3	57.5	56.8	63.2	68.5	657.9	12.9
Top 1%	-34.7	51.1	58.1	57.3	64.6	69.2	657.9	14.3
All	-8,773.0	34.1	42.4	44.4	51.4	60.3	15,654.5	217.7

Current-Year Marginal Tax Rates

Resource Group	min	q25	median	mean	q75	q90	max	std.dev
Bottom	-407.6	19.3	28.3	40.1	39.8	64.9	2,567.4	117.3
Second	3.6	26.8	30.3	31.3	35.1	40.1	237.6	11.0
Third	-2,054.6	28.5	32.2	33.0	37.8	40.2	103.9	32.0
Fourth	-18.6	28.7	34.2	34.2	39.1	41.4	131.6	8.8
Highest	-8.0	31.3	39.2	38.2	43.8	50.6	142.0	9.6
Top 5%	-8.0	38.2	43.2	42.8	48.7	52.7	82.6	9.2
Top 1%	-8.0	39.3	42.8	42.6	47.3	51.7	82.6	10.0
All	-2,054.6	27.4	32.3	35.4	39.4	45.0	2,567.4	41.5

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

	CY Baseline	CY Marg.	CY Diff	PV Baseline	PV Marg.	PV 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

	min	q25	median	mean	q75	q90	max	st.dev
Bottom	8.2	18.4	26.6	36.2	47.7	69.0	159.4	27.7
Second	6.1	11.5	17.2	28.8	34.4	63.9	206.2	29.4
Third	6.2	10.9	14.6	25.6	24.9	52.2	394.1	35.1
Fourth	6.0	11.9	14.0	17.2	17.1	27.7	132.2	11.5
Highest	5.9	13.5	15.5	16.2	17.6	21.4	219.9	8.5
Top 5%	6.0	13.5	16.2	16.8	18.7	21.6	219.9	10.6
Top 1%	6.0	12.3	17.6	17.5	21.6	26.0	98.3	9.0
All	5.9	12.1	15.2	21.9	21.2	38.1	394.1	21.5