

Using Microsimulation Modeling to Forecast Long-term Tax Revenues in North Carolina

METHODS & ANALYSIS PLAN

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Policy Question

Our policy question for the North Carolina Office of State Budget and Management's (OSBM) Demographic and Economic Analysis (DEA) unit is: **How will demographic changes in North Carolina over the next 20 years (2021–2040) affect state income and consumption tax revenues?**

Method Summary

To answer the policy question, DEA is interested in creating two microsimulation models to predict both future income and tax revenues.^a Microsimulation is a broad term for any model that uses data on individual households or people (termed “microdata”) to understand the effects of policies or policy reform on individual behaviors. Based on conversations with microsimulation analysts in the Congressional Budget Office (CBO) and with our client, we will use static microsimulation models for the project. Static microsimulation employs the following basic steps; see Appendix A for more detail on static microsimulation.¹

1. Assemble a base dataset with observations that include individual's demographic (i.e., race, ethnicity, age, and sex) and income or consumption expenditure information.
2. Weight the observations in the dataset, such that the weight indicates the number of individuals each observation represents.
3. Calculate future weights for each year of the projection period based on future demographic composition and economic trends.
4. Project income or consumption expenditure by applying weights for each year in the projection period to baseline observations.

^a Although we are technically projecting tax liabilities, we assume throughout this project that the aggregate individual tax liability is equal to total state tax revenue.

5. Apply tax calculators to the projected incomes or consumption to estimate income tax liability and consumption taxes paid for each observation.
6. Multiply tax liability (income) or taxes paid (consumption) for each observation by weights to calculate total predicted tax revenue.

Data

The below table indicates the data sources we will use for this project. For further detail on the contents of each dataset, see Appendix B.

Table 1.

Income	
Data Type	Data Source
Demographic Projections	NC State Demographer and American Community Survey (ACS)
Income and Tax Microdata	Current Population Survey (CPS)
Wage and Salary Income Growth	CBO's Budget and Economic Outlook
Proprietors' Farm Income Growth	CBO's Budget and Economic Outlook
Proprietors' Non-Farm Income Growth	CBO's Budget and Economic Outlook
Interest Income Growth	CBO's Budget and Economic Outlook
Rental Income Growth	CBO's Budget and Economic Outlook
Dividend Income Growth	CBO's Budget and Economic Outlook
Additional Tax Variables	TBD
High-Income Earners ^b	OSBM DEA
Consumption	
Demographic Projections	NC State Demographer and ACS
Consumer Expenditure Microdata	Consumer Expenditure Survey
Tourism Revenue Data	State Tourism report / Travel Industry group reports

^b The CPS does not include incomes above a certain amount, so we will have to artificially insert some individuals with incomes above this cutoff into our data set.

Analysis

Income Model

The first microsimulation model will predict future income tax revenue and will be built using the following steps: 1) create the base dataset, 2) weight the base dataset, 3) assemble projections, 4) revise DEA's tax calculator, 5) test the model, 6) apply projection weights, 7) grow incomes, and 8) apply the tax calculator to the dataset.

Create the base dataset. Data from the 2015-2019 CPS will be combined to group all five years in to one aggregate year, detailed further in Appendix C. This technique increases the number of observations of different base characteristics in the base year, which is more reflective of the total North Carolina population.^c All income variables will be adjusted to 2019 dollars using the Consumer Price Index.

The data also need to be corrected for topcoded earnings,^d which the CPS does to preserve privacy. We will work with our client to artificially create a representative sample of people with topcoded earnings, likely by taking the mean incomes of high earners and applying that income to all those individuals. Should this be infeasible, some literature exists on techniques for imputing topcoded earnings.^{2, 3, 4}

We will also create new columns in the dataset for relevant variables that the CPS does not record, such as IRA contributions, self-employed health insurance

^c This technique was suggested to us by a microsimulation expert at the Congressional Budget Office. See Appendix C for more information.

^d Topcoding refers to the censoring of income values of the highest earners in a longitudinal study to protect individuals' identities. For example, CPS reports anyone with dividend incomes over \$999,999 as \$999,999.

deductions, self-employed savings deductions, itemized deductions, child and dependent care expenses, and capital gains or losses. We will discuss with our client and with tax policy and microsimulation experts whether all variables above are necessary to include, as well as the best way to impute them, but likely options include 1) performing a statistical match to the IRS' national Statistics of Income (SOI) Public Use File; 2) adopting the mean value from North Carolina income tax summary statistics; or 3) working with our client to artificially create a sample of people with representative distributions of these variables.^{5, 6}

Weight the base dataset. The CPS has sample weights to 1) indicate the number of people that each dataset observation represents in North Carolina and 2) correct for sampling error. To bring the CPS estimates in line with existing North Carolina demographic data, new weights will be applied. We will group all people with the same age, race, and gender, sum their CPS weights together, and divide the weight in the state's demographic data by the summed CPS weight to get an alignment factor that accounts for differences between the summed CPS and total population figures. See Appendix D for more information.

Assemble projections. We will construct a dataset of the economic projections, listed in Table 1 above, for each year between 2015 and 2031. The CBO does not have detailed economic projections past 2031, so we will create our own projections for 2030 to 2040 using a time series regression on the 2022-2031 data from each category of income. We will then use that calculation to consistently grow income components from 2032 to 2040, creating a "CBO projection dataset."

Revise DEA's tax calculator. DEA has an existing tax calculator coded in SAS that uses information from actual NC tax filings. These tax data contain many variables that are not collected in the CPS and therefore not in our base dataset. We will either recode this calculator to assume any missing variable is zero, or assume a reasonable value suggested by our client. We will also recode the calculator to use the dataset's new population weights.

Test against base year. Once the base dataset, economic trend data, and tax calculator are assembled, we will test our model to see if it accurately predicts 2015-2019 tax revenue. Applying the tax calculator to the incomes of people in our base dataset and aggregating individuals' tax liabilities will result in a number that should match the amount of tax liability North Carolina saw in 2015, 2016, 2017, 2018, and 2019. We expect our predicted liability and the actual state tax revenues to be close, although the two numbers may differ because 1) our model may omit data on some income sources that are not available in the CPS, 2) people may underreport their incomes in the CPS, and 3) tax liability may not reliably translate in to tax revenue if some people do not pay their taxes.⁷ However, if our model predicts an unreasonably high or low values for income tax liability, this result will serve as a red flag for code review.

Apply projection weights. After checking the model, we will reweight the population in the dataset for each projection year, 2022-2040, based on the information in the demographic file. See Appendix D for more detail.

Grow incomes. For each projected year, all income components within the base dataset will be multiplied by the growth factor for that income type using the CBO projection dataset.

Apply the tax calculator. Finally, to project tax revenue in 2040, we will feed the base dataset, with adjusted weights and grown incomes, into the recoded tax calculator. The output of this step will produce a number that represents the aggregate tax liabilities of North Carolinians in 2040. We assume that tax liability equals tax revenue; estimating tax compliance is beyond the scope of this investigation.

Consumption Model

A second microsimulation model will be developed to estimate consumption tax revenues. This model uses consumer units (CUs) from the Consumer Expenditure Survey (CES) as the primary unit of analysis.^e This model will be built using the following steps: 1) create the base dataset, 2) weight the base dataset, 3) calculate and apply weights, 4) calculate propensity to consume, 5) grow incomes, 6) calculate spending by expenditure category, 7) calculate taxes by expenditure category, and 8) sum taxes paid across CUs.

^e BLS defines a consumer unit as either: (1) all members of a particular household who are related by blood, marriage, adoption, or other legal arrangements; (2) a person living alone or sharing a household with others, but who is financially independent; or (3) two or more persons living together who use their income to make joint expenditure decisions. (Consumer Expenditure Survey – Glossary, 2021. Accessed at: <https://www.bls.gov/cex/csxgloss.htm>)

Create the base dataset. Using the 2019 CES, we will create an indicator variable for each income/age group (a “set”).^f For example, all expenditure data from people aged 18-24 with \$60,000 will be flagged with a unique indicator code.

Weight the base dataset. The CES has sample weights to 1) indicate the number of people that each dataset observation represents in North Carolina and 2) correct for sampling error. To bring the CES estimates in line with existing North Carolina demographic data, we will apply new weights to the 2019 dataset. We will group observations by age, sum the CES weights in each age group, and divide the weight in the state’s demographic data by the summed CES weight to get an alignment factor, similar to the procedure done in the income tax microsimulation weighting. See Appendix D for more information.

Calculate and apply weights for projection years. We will use the State Demographer’s projections to calculate weights for year 2022-2040, which will be the ratios of the population size in each projection year to the reference year (2019) population for each age group. These weights will be applied to calculate the number of CUs that each observation in the dataset represents statewide. See steps 2 and 3 in Appendix D for more information.

Calculate propensity to consume for overall spending and for specific spending categories. For each observation, we will calculate 1) total spending as a share of

^f Race and gender have not been found to be significant predictors of consumption patterns. Therefore, we only focus on age and income in this analysis. He, Zheli, “Marginal Propensity to Consume: Penn Wharton Budget Model,” (Washington, DC: Bureau of Labor Statistics, 2018), <https://www.bls.gov/cex/ws2018-marginal-propensity-to-consume.pdf>

income and 2) spending on specific categories as a share of total spending.^g To predict spending patterns by each CU in future years we will calculate a weight for total spending (as a share of income) and spending by category (as a share of total spending) relative to the average values for the corresponding income group. For example, if the average propensity to consume for CUs in the \$70,000–80,000 income range is 75%, a CU with an income of \$75,000 that spends 90% of its income would have a weight of $\frac{0.9}{0.75} = 1.2$. This will preserve CU-specific expenditure patterns.

Grow incomes. We will use CBO’s personal income growth projections to increase incomes over the projection years, relative to the reference year (2019).

Calculate spending by expenditure category. For each CU in each year, we will multiply that CU’s new income by the average propensity to consume for 1) total household spending and 2) spending by category for the new income group. This calculation produces each CU’s predicted total expenditure for each category.

Calculate taxes by expenditure category. To calculate to sales taxes paid by each CU, we will:

- 1) Sum all expenditure on categories subject to sales taxes.^h
- 2) Adjust for the fact that CES reports data at the region level by multiplying this amount by $\frac{1}{1+\bar{t}}$, where \bar{t} is the average combined state and local tax rate

^g The specific spending categories to be calculated account for goods exempt from North Carolina’s sales tax (housing, medical service and prescription drugs, gasoline, and liquor) as well as those subject to excise taxes (tobacco and liquor) that go to the General Fund.

^h Goods exempt from sales taxes include housing, groceries, medical services and prescription drugs, gasoline, and liquor.

for states in CES Southern region (West Virginia, Virginia, North Carolina, South Carolina, Georgia, and Florida).

- 3) Multiply the amount from Step 2 by the North Carolina sales tax rate of 4.75%.

Excise taxes paid on tobacco and liquor will be calculated similarly, using their respective average tax rates.

Sum taxes paid across CUs. For each year, total taxes paid by each CU will be multiplied by the CU's weight and summed across all observations to calculate the total consumption taxes paid that year.

Deliverables

The goal of this project is to provide OSBM with a basic microsimulation model to inform long-term projections in income tax and consumption tax revenues. We will deliver two products from this project to DEA: a summary report and a SAS program.

Summary report. This report will summarize the results of the analysis, principally the projected tax revenues from personal income and consumption taxes from 2021 to 2040. Anticipated trends in other General Fund revenue sources will also be discussed to contextualize these findings. We will also highlight the elasticity of revenues from income tax and consumption taxes – that is, their growth relative to predicted growth in state GDP. The report will also provide a summary of the methods and data sources used, which will be adapted from this Methods & Analysis Plan, as well as assumptions and potential limitations of the underlying data.

Appendices will provide detailed methodology for creation of the datasets, construction of weights, and projection of demographic and economic trends.

SAS program. We will also provide DEA the clean and notated SAS code (DEA's preferred statistical software) used to construct the dataset, create base and projected weights, and impute additional demographic, economic, and tax variables. This file will allow their staff to update and revise the models as needed for future projections. DEA will also be able to run this SAS program on other datasets, including complete tax return records from the Department of Revenue.

Additional Considerations

Concerns and Mitigation Plan

A microsimulation model is built using multiple data sources, each of which introduce potential mismeasurement and bias. For example:

- CBO's economic forecasts may not account for future market shocks;
- Census Bureau's CPS collects self-reported data, leaving room for individuals to mis-report income information;
- BLS's Consumer Expenditure Survey does not offer state-level data for North Carolina, so we must assume the state follows regional spending trends; or
- OSBM's demographic projections may misestimate some elements of future demographic changes.

Our model is also built on assumptions that may not accurately reflect future trends. For example, our consumption tax model may assume that current consumption and savings rates continue throughout the next 30 years, even though

emerging research suggests that savings habits may be evolving for older adults.⁸ We are also using economic projections that may not accurately predict long-term consequences of the COVID-19 pandemic, particularly as they pertain to changes in consumer spending, employment, and migration.

To mitigate these concerns, we will create analytical assumptions based on available research and outline them at each stage of model development. We will also conduct sensitivity analyses by changing certain assumptions, such as the income growth rate or spending distributions, and re-running the model. We will report on tax revenues gathered in these multiple scenarios to increase the robustness of our analysis. While we cannot anticipate all future trends that may impact demographics, income, and consumer spending in North Carolina, we aim to build a flexible model that can be adapted over time to accommodate new data and trends.

Complementary Techniques

The modeling of personal income and consumption tax revenues described above constitute the bulk of our analysis. However, to form a more complete picture of North Carolina's tax revenue through 2040 and create a more comprehensive model of the effects of demographic changes, we also propose to estimate inter-state travel effects and estimate revenues from health insurance taxes.

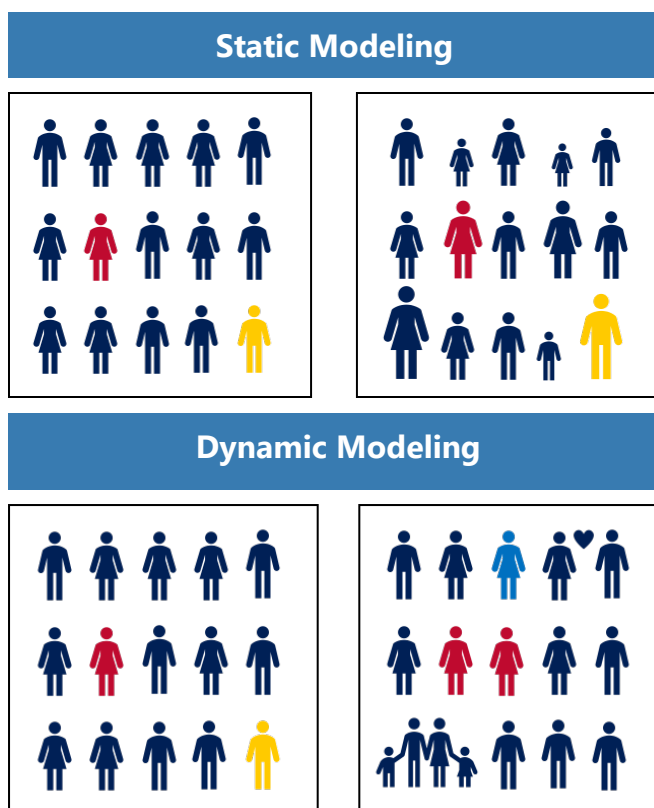
Estimate effects of inter-state travel on consumption tax revenues. Because our consumption tax model models in-state spending by in-state households, it does not consider out-of-state expenditure by these households or in-state expenditure by those residing outside of North Carolina. We will account for this discrepancy using data on the economic impacts of tourism in North Carolina and average tourist

expenditure in other states or nationwide, to estimate these values.⁹ However, if the net effect of these two phenomena is close to zero (i.e., that the amount of consumption taxes paid by North Carolina residents to other states is roughly equal to that paid by non-residents in North Carolina), we will exclude these calculations in our analysis.

Estimate revenues from taxes on health insurance premiums. Personal income and consumption tax revenues constituted 91% of tax revenue in Fiscal Year 2020. Of the remainder, six percent comes from corporate income and franchise taxes, on which the effects of demographic changes are not clear. However, the final three percent comes from a tax on insurance premiums. Demographic trends may play a significant role in determining patterns in insurance enrollment and premium payments. While comprehensive analysis of health insurance premium taxes merits its own project and is beyond the scope of this project, we may aim to provide some insight into the long-term trajectory of this revenue source to respond to stated interest from our client.

Appendix A: Overview of Static Microsimulation

Microsimulation models can either be static or dynamic in the way they age populations. In static models, the same “people” from the baseline dataset do not change. Their weights may change to reflect projected demographic or economic trends, but the same “people” are carried through the analysis. Conversely, dynamic models change the underlying population.



In *static microsimulations*, the beginning and ending dataset contain the same number of people. The distribution of characteristics does not change. Only the weights change to represent increases or decreases in the number of people with a given set of characteristics.

In *dynamic microsimulations*, the beginning and ending dataset differ. Individuals can die, be born, get married, have children, or lose their job. The distribution of characteristics changes from year to year. This type of modeling is more realistic but makes more rigid probability-based assumptions than static modeling.

These models probabilistically estimate the likelihood that an individual gets married, becomes unemployed, has a child, or dies, among other changes. Such a modeling structure allows different policies to interact with each other: someone’s likelihood of having children may change as they age or become wealthier, so tax cuts that increase incomes may also increase Child Tax Credit claims in future years.

Researchers typically use static models for more detailed simulations that take place within a generation. Dynamic models use simpler simulations with more assumptions but are more realistic over multiple generations because they account for more types of behavior changes than static models.¹⁰

Appendix B: Data Sources

Income Tax Model

CPS Microdata. The Current Population Survey (CPS) will provide the main microdata used in the base dataset. We will use demographic, income, and tax filing data and variables years 2015-2019ⁱ from the IPUMS CPS site.¹¹

Demographic Data. The primary source of demographic data is annual projections (2010–2050) of the number of North Carolina residents by age, race, and sex publicly available from the State Demographer. Ages in this data set are binned in 5- and 10-year ranges from age 20 to 84 (i.e., 25-34, 35-44, etc.). This data set disaggregates only by race (White, Black, Asian, and American Indian and Alaska Native) and not ethnicity (Hispanic or non-Hispanic). As a major demographic trend of interest is the increase in the Hispanic share of the population, we will disaggregate the share of those identifying as Hispanic for each racial group through imputation of additional data from the State Demographer and the American Community Survey (ACS). This data will be used to determine the weights assigned to observations in the CPS.

External Economic Projections. As part of its annual Budget and Economic Outlook (BEO), the Congressional Budget Office (CBO) publishes projections for the growth rates of taxable personal income, wage and salary income, and net positive long-term capital gains; a single growth rate for all other forms of taxable income can be calculated as a residual.¹² The most recent BEO offers quarterly and annual

ⁱ In 2014, the CPS used a different method to calculate incomes and we thus begin with 2015. We omit 2020 and 2021 data because of the potential for anomalous effects from the COVID-19 pandemic.

projections for years 2021-2031. CBO revises these annual estimates every six months as part of its annual Update to the Budget and Economic Outlook.¹³

CBO also produces less granular estimates of projected macroeconomic trends 30 years into the future, identified in the 10-year BEO.¹⁴ Reported variables include estimated GDP growth, labor force participation changes, real earnings per worker, and inflation. Although these projections do not offer specific estimates of how different components of taxable income will change after 2031, the trends in earnings growth can be used as a proxy and a reasonableness check when we extrapolate income growth projections using time series regressions on 2021-2031 BEO data.

Consumption Tax Model

BLS Consumer Expenditure microdata. The Bureau of Labor Statistics (BLS) publishes extensive Public Use Microdata (PUMD) that details consumer expenditures, income, savings, and demographic information such as age, race, ethnicity, and gender.¹⁵ This data is collected through the Consumer Expenditure Surveys (CES). While the data are extensive, BLS does not provide weights that allow the national survey to be mapped onto North Carolina consumers. OSBM has recommended using data from the Southern Region (West Virginia, Virginia, North Carolina, South Carolina, Georgia, and Florida) and assuming North Carolina consumption patterns follow those of the rest of the South.

External Economic Projections. CBO's Budget and Economic Outlook includes projections for how the consumer price index (CPI) will change in coming decades.¹⁶ This economic measure provides an estimation of how the prices for a fixed basket of goods will change over time, averaged across all regions and demographic groups.

These estimates are provided on a national level, without any disaggregation by demographic characteristics.

Demographic Data. Like our demographic data for the income tax model, our demographic projections are obtained from the State Demographer and cover 2010 to 2050. However, for the consumption tax model this data will only be disaggregated by age (using single year of age population estimates).¹⁷ This provides greater granularity in modeling changes in expenditure habits by age while recognizing that recent literature suggests there are not significant difference in average propensity to consume across racial groups.¹⁸

Appendix C: Process for Combining Sample Years in the Base CPS Dataset

To increase the sample size of our base dataset, we will merge five years of CPS data (2015-2019) by adjusting the dataset weights each year to account for different total yearly populations. Detailed steps for combining years in the base dataset are as follows:

1. **Generate CPS base weights for a given year** (i.e., number of people each CPS observation represents) by:
 - a. Creating a variable [set] for each set of demographic variables of interest (race, age, and sex) during that year and summing the CPS weights by [set] and year.
 - b. Multiplying the demographic set's weight for each year by the reciprocal of that set weight for 2019 to create a year weight [yearwt] for each [set] by year (therefore, [yearwt] = 1 for 2019).
 - c. Multiplying weights [asec] by corresponding [yearwt] and divide by 5 to produce [basewt] for each observation.
2. **Generate projection weights** (i.e., adjustments to the base weights to account for demographic growth and changes in projection years) that match aggregate population projections from the State Demographer, by:
 - a. Creating a variable [set] for each set of demographic variables of interest (race, age, and sex) to match base weights.

- b. Dividing the population for each projection year (2020–2040) by the reference year (2019) population to create a year weight [yearwt] for each [set] (*note this yearwt is different from the yearwt variable calculate in Step 1).^j
3. **Impute population growth rates for the Hispanic population**, and adjust weights for the non-Hispanic population accordingly, by
 - a. Calculating Hispanic and non-Hispanic share of the population for each race, by sex. All racial groups except “White” will be calculated together as they are not disaggregated in the State Demographer data. These data will come from the ACS.
 - b. For each race-sex group and for each projection year (2020–2040), divide the Hispanic and non-Hispanic share of the population by the corresponding share for the reference year (2019) to generate a weight for both Hispanic population growth [hispgrwth] and non-Hispanic growth [nonhispgrwth] for each year.
 - c. Merging growth weights with projection weights and multiply each [yearwt] with the corresponding [hispgrwth] or [nonhispgrwth] weight.

^j CPS does not sample individuals from every age-race-gender group (e.g., 29-female-Asian) in each year. In cases where the State Demographer data indicates the presence of a 29-year-old Asian female in a given year, but the base dataset does not contain anyone with that demographic set, we will instead assign that person to a similar group (i.e., 30-year-old Asian female) in the base dataset.

Appendix D: Process for Applying Demographic Weights

Detailed steps for applying demographic weights are as follows:

1. Start with the base demographic file and **calculate the yearly percent change** for each race/gender/age group. In the example on the right, the White

Female aged 45 population (“WF45”)

increased by 10% from 2021 to 2022 and by

18.2% from 2022 to 2023.

Demographic File				
Year	Race	Gender	Age	Number
2021	W	F	45	100
2022	W	F	45	110
2023	W	F	45	130

2. **Calculate the base alignment factor** to align CPS data to actual demographic base year data. If the CPS dataset shows two groups of WF45s (represented by “ABC” and “XYZ” in the Other Characteristics column) that each have a CPS weight of 25, the Alignment Factor is equal to the number of WF45s in the demographic file divided by the sum of the CPS weights for all WF45s. If each WF45 in the CPS represents 25 people, the alignment factor is $2 \left(\frac{100}{25+25} \right)$. The new 2021 weight for each group is then the alignment factor times the CPS weight ($25 * 2 = 50$).

Base CPS Dataset							
Year	Race	Gender	Age	Other Characteristics	CPS Weight	2021 Alignment Factor	New 2021 Weight
2021	W	F	45	ABC	25	2	50
2021	W	F	45	XYZ	25	2	50

3. **Multiply the new weight by the yearly percent change** from the demographic data file. The percent change from 2021-2022 is 10%, calculated above, and

the 2022-2023 percent change is 18.2%. The 2022 weight is then $50 + (50 * 10\%)$, or 55, and the 2023 weight is $55 + (55 * 18.2\%)$, or ~65.

Base CPS Dataset									
Year	Race	Gender	Age	Other Characteristics	CPS Weight	2021 Alignment Factor	New 2021 Weight	2022 Weight	2023 Weight
2021	W	F	45	ABC	25	2	50	55	65.01
2021	W	F	45	XYZ	25	2	50	55	65.01

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- ¹ Congressional Budget Office, “An Overview of CBO’s Microsimulation Tax Model,” accessed September 9, 2021, <https://www.cbo.gov/system/files?file=2018-06/54096-taxmodel.pdf>
- ² https://www.nber.org/system/files/working_papers/w19846/w19846.pdf#:~:text=Most%20researchers%20measuring%20long-term%20trends%20in%20earnings%20with,researchers%20using%20a%20multiple%20between%201.3%20and%201.5
- ³ <https://www.sciencedirect.com/science/article/abs/pii/S0165176510000881>
- ⁴ <https://www.cbo.gov/sites/default/files/cbofiles/ftpdocs/71xx/doc7164/2006-06.pdf>
- ⁵ <https://www.census.gov/content/dam/Census/library/working-papers/2004/demo/oharataxmodel.pdf>
- ⁶ <https://www.irs.gov/pub/irs-soi/06ohara.pdf#:~:text=This%20same%20method%20is%20applied%20to%20determine%20the,simulated%20separately%3B%20this%20section%20only%20discusses%20capital%20gains>
- ⁷ <https://www.irs.gov/taxtopics/tc652>
- ⁸ De Nardi, Mariacristina, Eric French, John Bailey Jones, and Rory McGee. “Why Do Couples and Singles Save During Retirement?” National Bureau of Economic Research, Working Paper 28828 (May 2021).
- ⁹ Visit North Carolina (a part of the Economic Development Partnership of North Carolina), 2019 Annual Report.
- ¹⁰ Urban Institute, “Static versus Dynamic Microsimulation,” accessed September 8, 2021, <https://boreas.urban.org/documentation/Static%20versus%20Dynamic%20Microsimulation.php>
- ¹¹ <https://cps.ipums.org/cps/>
- ¹² Congressional Budget Office, “The Budget and Economic Outlook: 2021 to 2031.” February, 2021. Accessed September 29, 2021. <https://www.cbo.gov/publication/56991>.
- ¹³ Congressional Budget Office, “An Update to the Budget and Economic Outlook: 2021 to 2031.” July, 2021. Accessed September 29, 2021. <https://www.cbo.gov/data/budget-economic-data>.
- ¹⁴ Congressional Budget Office, “The 2021 Long-Term Budget Outlook.” March, 2021. Accessed September 29, 2021. <https://www.cbo.gov/data/budget-economic-data>.
- ¹⁵ “Consumer Expenditure Surveys (CE) Public Use Microdata Home.” Accessed September 30, 2021. <https://www.bls.gov/cex/pumd.htm>.
- ¹⁶ Congressional Budget Office, “The 2021 Long-Term Budget Outlook.” March, 2021. Accessed September 29, 2021. <https://www.cbo.gov/data/budget-economic-data>.
- ¹⁷ State Demographer [North Carolina], “Sex and Single Years of Age (2000 – 2050),” County/State Population Projections, <https://www.osbm.nc.gov/facts-figures/population-demographics/state-demographer/countystate-population-projections#ProjectionData>
- ¹⁸ He, Zheli, “Marginal Propensity to Consume: Penn Wharton Budget Model,” (Washington, DC: Bureau of Labor Statistics, 2018), <https://www.bls.gov/cex/ws2018-marginal-propensity-to-consume.pdf>