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

METHODS & ANALYIS 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 long-term microsimulation models to predict both future income and tax revenues.[[1]](#footnote-2) 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 and with our client we will use static microsimulation models for the project, which employs the following basic steps: (see Appendix A for more detail).[[2]](#endnote-2)

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 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.
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 |
| Income and Tax Microdata | | Current Population Survey |
| 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 |
| Capital Gains Income | | TBD |
| High-Income Earners[[3]](#footnote-3) | | OSBM |
| **Consumption** | | |
| Demographic Projections | | NC State Demographer |
| Consumer Expenditure Microdata | | Bureau of Labor Statistics, Consumer Expenditure Survey |
| Tourism Revenue Data[[4]](#footnote-4) | | State Tourism report / Travel Industry group reports |
|  | |  |
|  | |  |

# Model Construction

## Income Model (Sam)

The first microsimulation model will predict future income tax revenue and will be built using the following steps: 1) assemble the base dataset, 2) weight the base dataset, 3) assemble projections, 4) alter DEA’s tax calculator, 5) test the model, 6) “age” the dataset, 7) adjust incomes, and 8) apply the tax calculator to the dataset.

**Assemble the base dataset.** Data from the 2015-2019 CPS will be “collapsed” to group all five years in to one aggregate year. This technique provides more people with different base characteristics in the base year, which is more reflective of the total North Carolina population.[[5]](#footnote-5) [[Tom’s text here]]. All income variables will be adjusted to 2019 dollars using the Consumer Price Index.

The data also need to be corrected for topcoded earnings,[[6]](#footnote-6) which the CPS does to preserve privacy. We will work our client to artificially create a representative sample people with topcoded earnings, likely by taking the mean incomes of high earners and applying that income to all of those individuals. Should this be infeasible, some literature exists on methods for imputing topcoded earnings.[[7]](#endnote-3), [[8]](#endnote-4), [[9]](#endnote-5)

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 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 industry 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) work with our client to artificially create a sample of people with representative distributions of these variables.[[10]](#endnote-6), [[11]](#endnote-7)

Last, we will remove nonfilers from the dataset before we begin our analysis, as per client recommendation.

**Weight the base dataset.** The CPS has sample weights that correct for sampling error based on known population-level demographic characteristics such as age, race, sex, and ethnicity. 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.

**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 projections past 2031, so we will take the average percent increase in each category between 2022 and 2031 and use that calculation to consistently grow income components from 2032 to 2040 (the “CBO projection dataset”).

**Alter DEA’s tax calculator.** DEA has an existing programmed tax calculator that uses information from actual tax forms, meaning it contains many variables that we do not have 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 weights.

**Test against base year.** Once the base dataset, tax calculator, and economic trend data are assembled, we will test our model to see if it accurately predicts 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 2019. We expect our predicted liability and the actual 2019 state tax revenue to be close, although the two may differ because 1) our model may omit data on some income sources because we cannot get those data, 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.[[12]](#endnote-8) However, if our model predicts an unreasonably high or low value for 2019 income tax liability, we will know that our model may need adjustments.

“**Age” the dataset.** To “age” the dataset,we will reweight the people in dataset each year based on the information in the demographic file. See Appendix C for more detail.

**Adjust 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, roughly equivalent to households) as the primary unit of analysis. Development of this model will follow seven steps:

**Create the base data set.** Using the Consumer Expenditure Survey (CES), we will group individual’s expenditure data based on their ages and incomes, as well as create a variable that identifies income group by age.[[13]](#footnote-7) For example, all expenditure data from White people aged 18-24 will be aggregated in to one group.

**Weight observations.** The CES has sample weights that correct for sampling error based on known population-level demographic characteristics such as age, race, sex, and ethnicity. To bring the CES estimates in line with existing North Carolina demographic data, new weights will be applied. We will sum the CPS weights for the age groups we construct and divide the weight in the state’s demographic data by the summed CES weight to get an alignment factor.

**Calculate weights for projection years to “age” the population.** We will use demographic projections from the State Demographer to calculate 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 represents.

**Calculate weights for spending patterns**. We will calculate marginal propensity to consume (MPC) as total spending divided by income (over a standardized period of time) for each age-income group. We will also calculate spending as a share of total spending (by income-age group) for six specific expenditure categories: housing, groceries, medical services and prescription drugs, gasoline, tobacco, and liquor. These categories account for goods exempt from North Carolina’s sales tax as well as those subject to excise taxes that go to the General Fund. Finally, we will calculate weights for both MPC and share of expenditure by category by dividing these for each observation by their average value for the age and income group. Doing this preserves unique expenditure patterns of each observation when MPC is adjusted to account for income growth.

**Grow incomes.** We will use data from the CBO to project income growth differentially by age over the projection years. Using aggregate income projections, we will calculate income growth rate (relative to the reference year) for each observation for each year of the projection period.

**Calculate spending and taxes by expenditure category.** For each observation in a given year, we will multiply the new income by both the average MPC and share of expenditure by category for the new income group. This calculation produces the total expenditure for each category. Total spending less expenditure on housing, groceries, medical services and prescription drugs, gasoline, and liquor is considered to be inclusive of the state’s 4.75% sales tax. Therefore, this amount will be multiplied by 1 / 1.0475 to calculate to sales take paid by the CU. Excise taxes paid on tobacco and liquor will be calculated similarly.

**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.

# Analysis

## Data Summary

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. In addition to the model itself, we will provide annotated SAS code such that OSBM can revise and add onto this model in the future. As conditions and needs evolve, we expect OSBM to use its additional resources and data access to update the tool with more complete tax collection data from the Department of Revenue, demographic projections, and tax policy changes.

Beyond the statistical model, we will also provide analysis regarding the potential impacts of our projections and sources of uncertainty. We will review relevant literature and consult experts in the field to explain the implications of the changes in tax revenue that may result from changing state demographics.

## Complementary Techniques

1. Other techniques used to complement the analysis (Tom)

The modeling of person 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 of the effects demographic changes, we also propose to do the following:

* Estimate effects of inter-state travel on consumption tax revenues. Because our consumption tax model using North Carolina households (or CUs) as the unit of analysis, it does not take into account out-of-state expenditure by these households or in-state expenditure by those residing outside of North Carolina. Although it may not be an unreasonable assumption to assume that the net effect of these two phenomena is zero (i.e., that the amount of consumption taxes paid by North Carolina residents to other states is exactly equal to that paid by non-residents in North Carolina), we propose to adjust for this by using data on the economic impacts of tourism in North Carolina as well as average tourist expenditure in other states or nationwide.[[14]](#endnote-9)
* Estimate revenues from taxes on health insurance premiums. Although
  1. Describe the paper that will accompany it (our value add: showing potential magnitude by which NC revenue will change/fall, detailing potential trends to watch out for, etc.)

## 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 may have sampling error in North Carolina;
* BLS’s Consumer Expenditure Survey does not offer state-specific data for North Carolina, so we must assume the state follows regional spending trends; or
* OSBM’s demographer 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.[[15]](#endnote-10) We are also leveraging 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 conduct sensitivity analyses of various assumptions to understand how changes to these assumptions alter the model’s projections. 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 adapt over time to accommodate new data and trends.

# Deliverables

The final output of this project will involve two components which will be delivered to DEA.

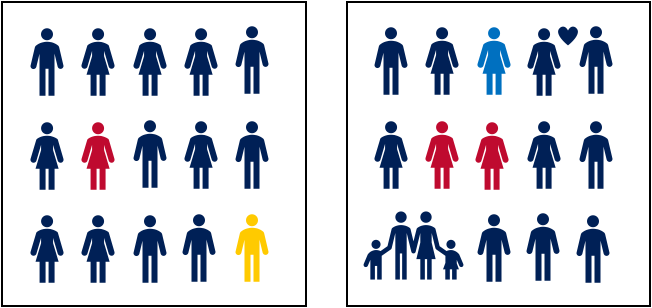
1. **Summary report.** This report will summarize the results of the analysis, principally the projected tax revenues from personal income and consumption taxes from 2021 to 2040. Anticipated trends in other General Fund revenue sources will also be discussed to contextualize these findings. Particular emphasis will also be placed on understanding the elasticity of income and consumption tax revenues – 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. Annexes will provide detailed methodology for creation of the data set, construction of weights, and projection of demographic and economic trends.
2. **SAS program.** The code used to construct the dataset, create base and projected weights, and impute additional demographic, economic, and tax variables onto the data set will written in SAS (or transferred to SAS if another statistical program is initially used). The SAS program will be cleaned and include detailed descriptions of the various computation steps. SAS is the preferred statistical software for DEA, which will be able to update and revise as needed for future projections. DEA will also be able to run this SAS program (with minimal adaption) on other datasets, including complete tax return records from the Department of Revenue, which are not available for us to use as non-state employees. Use of this more detailed and complete data set should provide more accurate projections.

# Appendix A.

Static versus Dynamic 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 *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.



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

**Static Modeling**



**Dynamic 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.[[16]](#endnote-11)

# Appendix B.

Data Sources

## Income Taxes

**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 10-year ranges from age 25 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

This data will be used to determine the weights assigned to observations in the CPS. Given the structure of this data,

**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 2015-2019[[17]](#footnote-8) from the IPUMS CPS site.[[18]](#endnote-12)

**External Economic Projections.**

As part of its annual Budget and Economic Outlook, CBO publishes projections for the growth rates of taxable personal income, wage and salary income, net positive long-term capital gains; a single growth rate for all other forms of taxable income can be calculated as a residual.[[19]](#endnote-13) The most recent Outlook offers quarterly and annual projections for years 2021-2031. CBO revises these annual estimates after six months as part of its annual Update to the Budget and Economic Outlook.[[20]](#endnote-14)

CBO also produces less-granular estimates of macroeconomic trends, projecting trends identified in the 10-year Budget and Economic Outlook 30 years into the future.[[21]](#endnote-15) 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.

## Consumption Taxes

**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.[[22]](#endnote-16) 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 crosstabs created that the regional level, 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.[[23]](#endnote-17) 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.

**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) and sex.[[24]](#endnote-18) 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.[[25]](#endnote-19)

# Appendix C.

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.
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. (100/(25+25)). The new 2021 weight for each group is then the alignment factor times the CPS weight (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.



**Step 1: Generate base weights (i.e. number of people each CPS observation represents)**

*Motivation and considerations*

* *Merging of five years of CPS data (to increase sample size) requires adjusting weights by year to account for different total population in each year*
* *Not all population groups are sampled by CPS in each year and, therefore, adjusting weights across years requires imputation*

Using: CPS microdata file

* 1. Create variable [set] for each set of demographic variables of interest (race, age, and sex)
  2. Sum weights [asec] by [set] and year to create a variable [asecwtsum]
  3. Multiply the set 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)
  4. Multiply weights [asec] by corresponding [yearwt] and divide by 5 to produce [basewt] for each observation

**Step 2: Generate projection weights (i.e., adjustment to base weights to account for demographic growth and changes in projection years)**

*Motivation and considerations*

* *Weights need to be adjusted to account for future population growth and demographic trends*
* *Sum of weights for future years must match aggregate population projections from State Demographer*

Using: NC State Demographer, *County/State Population Projections*, “Sex, Race, Age Groups (2000-2050)”

* 1. Create variable [set] for each set of demographic variables of interest (race, age, and sex) to match base weights
  2. Divide 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)

**Step 3: Impute population growth rates for the Hispanic population and adjust weights for the non-Hispanic population to account for this**

*Motivation and considerations*

* *NC State Demographer population projections do not incorporate Hispanic/Latino share of the population*

Using: NC State Demographer, *County/State Population Projections*, “Sex, Race, Age Groups (2000-2050)”

* 1. Calculate Hispanic and non-Hispanic share of the population for each race, by sex (*note that all racial groups except “White” will be calculated together as they are not disaggregated in the State Demographer data)*
  2. 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
  3. Merge growth weights with projection weights and multiply each [yearwt] with the corresponding [hispgrwth] or [nonhispgrwth] weight

1. 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. [↑](#footnote-ref-2)
2. 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> [↑](#endnote-ref-2)
3. The CPS top-codes incomes above a certain amount, so we will have to artificially insert some individuals with incomes above this into our data set. [↑](#footnote-ref-3)
4. Per conversations with OSBM, if out-of-state purchases by North Carolinians roughly equal in-state purchases by non-North Carolinians, we can ignore this type of spending in our model. [↑](#footnote-ref-4)
5. This technique was suggested to us by a microsimulation expert at the Congressional Budget Office. [↑](#footnote-ref-5)
6. 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. [↑](#footnote-ref-6)
7. 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 [↑](#endnote-ref-3)
8. https://www.sciencedirect.com/science/article/abs/pii/S0165176510000881 [↑](#endnote-ref-4)
9. https://www.cbo.gov/sites/default/files/cbofiles/ftpdocs/71xx/doc7164/2006-06.pdf [↑](#endnote-ref-5)
10. https://www.census.gov/content/dam/Census/library/working-papers/2004/demo/oharataxmodel.pdf [↑](#endnote-ref-6)
11. 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. [↑](#endnote-ref-7)
12. https://www.irs.gov/taxtopics/tc652 [↑](#endnote-ref-8)
13. Age and income are the two strongest predictors of consumption levels and types. Thus, we only focus on those demographic characteristics in this analysis. [SOURCE, @Tom?] [↑](#footnote-ref-7)
14. Visit North Carolina (a part of the Economic Development Partnership of North Carolina), 2019 Annual Report. [↑](#endnote-ref-9)
15. 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). [↑](#endnote-ref-10)
16. Urban Institute, “Static versus Dynamic Microsimulation,” accessed September 8, 2021, <https://boreas.urban.org/documentation/Static%20versus%20Dynamic%20Microsimulation.php> [↑](#endnote-ref-11)
17. 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 coronavirus. [↑](#footnote-ref-8)
18. https://cps.ipums.org/cps/ [↑](#endnote-ref-12)
19. Congressional Budget Office, “The Budget and Economic Outlook: 2021 to 2031.” February, 2021. Accessed September 29, 2021. https://www.cbo.gov/publication/56991. [↑](#endnote-ref-13)
20. 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>. [↑](#endnote-ref-14)
21. Congressional Budget Office, “The 2021 Long-Term Budget Outlook.” March, 2021. Accessed September 29, 2021. <https://www.cbo.gov/data/budget-economic-data>. [↑](#endnote-ref-15)
22. “Consumer Expenditure Surveys (CE) Public Use Microdata Home.” Accessed September 30, 2021. https://www.bls.gov/cex/pumd.htm. [↑](#endnote-ref-16)
23. Congressional Budget Office, “The 2021 Long-Term Budget Outlook.” March, 2021. Accessed September 29, 2021. <https://www.cbo.gov/data/budget-economic-data>. [↑](#endnote-ref-17)
24. State Demographer [North Carlina], “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 [↑](#endnote-ref-18)
25. 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 [↑](#endnote-ref-19)