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Exploration of Technical Developments and Data Sources that May Have Implications for Long-Range Transport Planning in Virginia

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Final Report VTRC 27-R06

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16. Abstract:

VTrans is the Commonwealth of Virginia's statewide multimodal transportation plan. Virginia's Office of Intermodal Planning and Investment maintains the plan under the supervision of the state's Commonwealth Transportation Board. The plan's methodology uses several VTrans "trend trackers" that are quantifiable metrics updated annually; "macrotrends," which are emerging patterns of change; and Commonwealth Transportation Board objectives, or qualitative targets for which the Office of Intermodal Planning and Investment defines various metrics. The research reported herein supported the Office of Intermodal Planning and Investment's mission through three tasks related to these trackers, macrotrends, and objectives: (1) compile statistical series, historical values, and future forecasts to represent seven trend trackers in the VTrans framework; (2) estimate the differences between forecast and observed values for population and employment; and (3) investigate the possible means of using one or more of the trend trackers in a planning application. Forecast data purchased from Woods & Poole Economics, Inc., coupled with data from publicly available sources and a review of the literature, formed the basis of the analysis.

The data from Woods & Poole support several VTrans trend trackers pertaining to population, employment, growth of professional and technical services, and population aged 65 and older. For instance, during 2020 through 2040, Virginia's population aged 65 and older is forecast to grow at an annual rate of 2.02%—nearly three times the forecast annual rate of the total population (0.69%). In addition, an analysis of input-output expenditures suggests that summing employment in three sectors—wholesale trade, retail trade, and transportation and warehousing—may support one of the trend trackers for macrotrend 5, the number of jobs in goods movement-dependent industries.

Woods & Poole generate forecasts of future population, employment, and personal income statistics for 105 regions in Virginia, each consisting of one county, one city, or one county plus one or two small cities and defined by the Bureau of Economic Analysis for statistical purposes. Population forecasts generated from 2014 to 2022 showed root mean squared differences between the forecast and the finalized estimate (2 years *ex post*) ranging from less than 1% to 10.20%, with population forecasts of more remote future years (e.g., 6 to 8 years away) tending to have larger errors than forecasts of closer impending future years (e.g., 1 to 2 years away). Employment forecasts generated from 2014 to 2022 showed root mean squared differences between the forecast and the finalized estimate ranging from 2.63% to 21.18%. Employment forecasts of more remote years tended to have larger errors; however, this pattern was much "noisier" than the pattern in the population forecasts. Personal income forecasts exhibited a quantitative performance similar to that of the employment forecasts.

This report found four examples of ways in which local planners might employ the VTrans data as a planning resource: (1) use population forecasts to predict if and when density for rural areas will increase to a level sufficient to support fixed-route bus service; (2) use income forecasts to estimate the fraction of households that will not have access to a vehicle; (3) use income and population density forecasts to predict changes in right-of-way costs; and (4) use employment and population forecasts to forecast changes in the ratio of the number of jobs divided by the number of residents (i.e., jobs-housing balance).

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FINAL REPORT

EXPLORATION OF TECHNICAL DEVELOPMENTS AND DATA SOURCES THAT MAY HAVE IMPLICATIONS FOR LONG-RANGE TRANSPORT PLANNING IN VIRGINIA

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In Cooperation with the U.S. Department of Transportation
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ABSTRACT

VTrans is the Commonwealth of Virginia's statewide multimodal transportation plan. Virginia's Office of Intermodal Planning and Investment maintains the plan under the supervision of the state's Commonwealth Transportation Board. The plan's methodology uses several VTrans "trend trackers" that are quantifiable metrics updated annually; "macrotrends," which are emerging patterns of change; and Commonwealth Transportation Board objectives, or qualitative targets for which the Office of Intermodal Planning and Investment defines various metrics. The research reported herein supported the Office of Intermodal Planning and Investment's mission through three tasks related to these trackers, macrotrends, and objectives: (1) compile statistical series, historical values, and future forecasts to represent seven trend trackers in the VTrans framework; (2) estimate the differences between forecast and observed values for population and employment; and (3) investigate the possible means of using one or more of the trend trackers in a planning application. Forecast data purchased from Woods & Poole Economics, Inc., coupled with data from publicly available sources and a review of the literature, formed the basis of the analysis.

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FINAL REPORT

EXPLORATION OF TECHNICAL DEVELOPMENTS AND DATA SOURCES THAT MAY HAVE IMPLICATIONS FOR LONG-RANGE TRANSPORT PLANNING IN VIRGINIA

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INTRODUCTION

The Office of Intermodal Planning and Investment (OIPI), an independent agency within the Transportation Secretariat of the Commonwealth of Virginia, is charged with preparing and updating VTrans, the Commonwealth's statewide multimodal transportation plan (OIPI, 2024a). The Commonwealth Transportation Board (CTB) reviews and approves the plan. OIPI publishes and updates several documents in support of the plan.

Components of VTrans Documentation

Two documents—*Socio-Demographic Changes*, one of four "megatrends" in the VTrans framework, and *Long-Term Risk and Opportunity Register*—serve as references for CTB and OIPI (OIPI, 2024b, 2025a). Both publications draw from population and employment trends and forecasts described in the *VTrans Technical Guide: Development and Monitoring of Long-Term Risk and Opportunity Register* (OIPI, 2025b).

The first step of the VTrans methodology recognizes four megatrends defined as "powerful and transformative forces" (OIPI, 2025a). Within each of these megatrends, the first step recognizes one or more specific macrotrends, described as "emerging patterns of change" (OIPI, 2025a). The first step assigns two or more specific metrics to each macrotrend to serve as trend trackers. The second step of the VTrans methodology recognizes five CTB goals. It associates two or more objectives, also called metrics, with each goal. The third step of the methodology identifies a range of potential effects of each megatrend on each goal objective. The fourth step of the VTrans methodology, based on feedback from policymakers and stakeholders, generates the *Long-Term Risk and Opportunity Register*. The register maintains a list of risks and opportunities defined as sources of uncertainty with respect to meeting CTB goals. A risk is defined as a potential negative effect, and an opportunity is defined as a potential positive impact. Each risk or opportunity in the list depends on the future evolution of one of the macrotrends. As of the writing of this report, the register lists nine risks and 10 opportunities, but these publications are living documents subject to additions or modifications. The fifth step of the VTrans methodology tabulates the trend trackers annually to report to CTB.

Background

The Virginia Transportation Research Council (VTRC), the research arm of the Virginia Department of Transportation (VDOT), has supported VTrans by assessing current levels of specific sociodemographic variables that OIPI uses for state-level transport planning and by determining past and future trends in these variables.

For several years, most recently in 2023, VTRC produced updates to the historical and forecasted future population and employment statistics that constitute four trend trackers under megatrend 4, *Socio-Demographic Changes* (Moruza and Gillespie, 2023). Moruza and Gillespie (2023) produced a technical assistance memorandum that contained an exploratory literature review and some exploratory analyses of the population and employment statistics; some of the analyses included one additional variable—land area. That portion of the memorandum had a precedent in previous VTRC work, for example, in Bhairavabhatla et al. (2020). The customers of the 2023 technical assistance memorandum accepted the researchers' offer to conduct a larger project that provides more exploratory analysis.

PURPOSE AND SCOPE

The purpose of this research was to give OIPI resources to update the trackers in the VTrans frameworks and to identify ways planners could use the VTrans resources. This study had three objectives:

1. Compile statistical series, historical values, and future forecasts to represent trend trackers in the VTrans framework. These data are essential and routine components of the VTrans statistics available to CTB and OIPI.
2. Estimate the margin of uncertainty in previous estimates of future employment statistics and in their estimates of the most recent past values. Such estimates help ensure that future consumers of the VTrans trend trackers understand the confidence interval to be expected around these estimates.
3. Identify possible means of using one or more of the trend trackers for planning applications.

Because OIPI required these data, the scope automatically included data for trend trackers relating to population, employment, growth of professional and technical services, population aged 65 and older, and income.

METHODS

The researchers grouped the exploratory analysis into three tasks:

1. Develop socioeconomic trends.
2. Assess forecast errors in the purchased dataset.
3. Identify planning-related applications of the trend trackers.

Task 1. Develop Socioeconomic Trends

The first task was to compile key statistics and review supporting literature that might inform the interpretation of those statistics. The research team compiled time series, comprising both historical values and future forecasts, to represent trend trackers within the VTrans framework.

Four of the time series were compiled in essentially the same manner as they have been compiled in previous updates of VTrans, which was to represent the same six trend trackers that they have represented before. The total number of jobs in each jurisdiction represented Employment, trend tracker 3 of 4 for macrotrend 10, Population and Employment Shift. The number of jobs in the professional and technical services sector in each jurisdiction represented the Number of STEM Jobs, or trend tracker 2 of 2 for macrotrend 7. The proportion of jobs in the professional and technical services sector in each jurisdiction, expressed as a ratio between the number in the sector and the total number of jobs, represented the Share of Professional Services Jobs in Total Employment, trend tracker 1 of 2 for macrotrend 7, and the Growth of the Professional Services Industry. The total number of residents in each jurisdiction represented Population, trend tracker 2 of 4 for macrotrend 10, Population and Employment Shift. The total number of residents aged 65 and older in each jurisdiction represented the Number of Virginians Age 65+, trend tracker 1 of 2 for macrotrend 9, Growth of the Age 65+ Cohort. The proportion of residents aged 65 and older in each jurisdiction, expressed as the ratio between the number of residents aged 65 and older and the total number of residents, represented the Share of Age 65+ in the Total Population, trend tracker 2 of 2 for macrotrend 9, Growth of the Age 65+ Cohort.

Two additional income time series were compiled experimentally. The total personal income and the mean household income in each jurisdiction were studied as possible candidates to represent Income, trend tracker 4 of 4 for macrotrend 10, Population and Employment Shift.

Several sectoral subcategories of the employment time series were studied as possible candidates to represent the Number of Jobs in Goods Movement-Dependent Industries, trend tracker 4 of 4 for macrotrend 5, Growth of E-commerce.

The researchers used two sets of population estimates—one set purchased from Woods & Poole Economics, Inc. (2024) and one set published by the Weldon Cooper Center for Public Service (hereafter, Cooper Center [2024]). The Woods & Poole dataset contained 122 files of historic and forecast sociodemographic features of Virginia counties and independent cities and towns from 1975 to 2060. The Cooper Center maintains a series of historical population counts and future forecasts. The research team also used an employment and income series from Woods

& Poole and block group-level population data from the U.S. Census Bureau. This task entailed tabulating population, employment, and income data at the county and city levels, the planning district level, and the VDOT construction district level, plus creating tables, charts, and graphs to reveal patterns in the data as comprehensibly as possible.

In parallel with the previous compilations, the researchers examined literature focusing on three topics. The first topic was (1) the measure of local residential turnover happening beneath the surface of county- and city-level population trends, (2) the measure of local demographic change, such as neighborhood gentrification, happening beneath the surface of county- and city-level trends in income and other demographic indicators, and (3) the interplay between these two local phenomena.

A second literature examination entailed using published expenditure data from the U.S. Department of Commerce to make inferences about which sectors in the Virginia economy were most dependent on goods or freight movement.

The third topic involved the available literature bearing on how the emergence of advanced artificial intelligence (AI) technologies, such as large language models (LLMs), has influenced employment projections or may influence them in the future. The researchers examined published literature from the U.S. Bureau of Labor Statistics (BLS), the Census Bureau, and refereed journal publications to determine first how BLS makes national employment projections and then how these projections address AI adoption in particular. Then, the research team examined the lessons learned from previous national-level forecasts that also sought to incorporate the emergence of new technologies. In summary, the team aimed to determine the effect that generative AI, such as LLMs, may have on the number or type of jobs in certain sectors of Virginia's economy.

Task 2. Assess Forecast Errors

The second task estimated the margin of error in the Woods & Poole population, employment, and income forecasts by comparing the forecasts in earlier editions of the Woods & Poole dataset with the realized historical values recorded in later editions of the Woods & Poole dataset. Woods & Poole deem the values for the year of publication and for the previous year to be "forecasts" because their established historical values depend on government data that are published with a lag of up to 2 years. The second task entailed computing and tabulating the errors in the forecasts at each lag length. The shortest observable lag length was +1, from the estimate Woods & Poole published 1 year *after* the year to which the estimate applied. Given the Woods & Poole editions available to the researchers, the longest observable lag length was -8, from the estimate published 8 years *before* the year to which the estimate applied. These computations provided a measure of the amount of uncertainty that exists in a given year of Woods & Poole's forecasts in the population, employment, and income categories.

Task 3. Explore Planning-Related Applications

The final task investigated possible means of using one or more of the trend trackers compiled in Task 1 in a planning application. The VTrans framework is tailored to the needs of CTB and OIPI. Task 3 explored four possible applications for planners. The researchers used the aforementioned Woods & Poole and Cooper Center datasets along with Census Bureau block group-level population counts. The first exploratory application studied population density as an indicator of the cost-effectiveness of fixed-route bus service. The second application studied household income as an indicator of a household's likelihood of owning no motor vehicle. The third application used population and personal income statistics as regressors to model and to forecast average real estate prices—a statistic for which forecasts are not regularly available. The fourth application studied employment and population forecasts as proxies for the jobs-housing ratio—another statistic for which forecasts are not regularly available.

RESULTS AND DISCUSSION

The results are grouped in three sections that correspond respectively to the three tasks described in the Methods section.

Task 1. Socioeconomic Trends

VTrans identifies certain statistics as meaningful quantitative measures of the 10 macrotrends that it recognizes. These macrotrends are called the trend trackers. For several years in a row, VTRC has assisted OIPI in compiling historical and forecasted future values for six of the trend trackers.

This study's first task entailed compiling the values of the six trend trackers, which VTRC has compiled on previous occasions. Three of the trend trackers concerned population, and three concerned employment. This task developed a provisional method for defining a fourth employment statistic, which may answer the definition of another of the trend trackers in the VTrans framework. Task 1 also included compilation of the values of an income statistic, which happens to be included in the dataset that OIPI purchased for the purpose of making VTrans updates and which may answer the definition of another trend tracker in the VTrans framework. Task 1 also entailed reviewing literature on a few issues—residential turnover, adoption of advanced AI, and demographic change—which add nuance to the interpretation of the trend trackers. The following seven sections present the results:

- Population.
- Employment.
- The number of jobs in industries dependent on the movement of goods.
- Employment projections since the emergence of LLMs.
- Personal income.
- The likelihood of demographic change versus the speed of transport investment.
- The effect of transport investment on the likelihood of demographic change.

Five counties in Virginia have chosen to take part in the activities of *two* of the planning district commissions. When tallying population, employment, and income subtotals for the planning districts, authors of past VTRC studies in support of the VTrans exercise have assigned each of these five counties to only one planning district. They have done so to ensure that the planning district subtotals in the tables and charts sum to no more than 100% of the state total. This study's authors imitated that practice. Franklin County's statistics appear only in the subtotals of the Roanoke Valley-Alleghany Regional Commission (planning district 5), although the county also works with the West Piedmont Planning District Commission (district 12). Charles City County and Chesterfield County's statistics appear only in the subtotals of the Richmond Regional Planning District Commission (district 15), although these two counties also work with the Crater Planning District Commission (district 19). Gloucester County's statistics appear only in the subtotals of the Middle Peninsula Planning District Commission (district 18), although the county also works with the Hampton Roads Planning District Commission (district 23). Surry County's statistics appear only in the subtotals of the Crater Planning District Commission (district 19), although the county also works with the Hampton Roads Planning District Commission (district 23).

Population

Three VTrans trend trackers relate to the population in Virginia. Macrotrend 9, Growth of the Age 65+ Cohort, recognizes two trend trackers. These trackers are the Number of Virginians with Age 65 or Higher and the Share of the Age 65+ Cohort in the total population. Macrotrend 10, Population and Employment Trends, recognizes four trend trackers, one of which is Population, meaning the total population.

Two sets of population estimates were compiled and studied. The primary population estimates came from the Woods & Poole dataset. Population calculations in this report come from the Woods & Poole dataset except where otherwise noted. The secondary population estimates came from the Cooper Center dataset. A member of the technical review panel noted that certain provisions in the Code of Virginia refer specifically to the Cooper Center's population statistics. A provision that applies to the Northern Virginia Transportation Authority (33.2-2504) prescribes the use of the population series published by the Cooper Center. A provision that applies to the Hampton Roads Transportation Commission (33.2-2604) prescribes the same (Legislative Information System, 2024).

This study added to the population compilations a brief literature review on the residential turnover that underlies changes in population.

The Rate of Population Change

Population growth is an important driver of travel demand growth generally and is an explanatory factor of the growth of specific travel demand measures, such as vehicle miles traveled.

Table 1 shows the average annualized growth rates of total population for the Commonwealth, each VDOT construction district, and each planning district during the 20-year periods beginning in 1980, 2000, 2020, and 2040. The rates are realized historical rates for the former two periods and Woods & Poole forecast rates for the latter two periods.

Table 1. Annualized Growth Rate of Total Population

Location	1980–2000	2000–2020[a]	2020–2040	2040–2060
Virginia Total	1.412%	0.981%	0.688%	0.716%
VDOT Construction Districts				
Fredericksburg	2.710%	1.698%	1.215%	1.162%
Northern Virginia	2.509%	1.675%	1.066%	1.145%
Culpeper	1.801%	1.437%	0.882%	0.810%
Richmond	1.294%	1.091%	0.682%	0.589%
Staunton	1.188%	0.970%	0.600%	0.582%
Hampton Roads	1.233%	0.468%	0.353%	0.335%
Salem	0.650%	0.331%	0.277%	0.265%
Lynchburg	0.230%	0.171%	0.159%	0.152%
Bristol	– 0.330%	– 0.398%	– 0.179%	– 0.148%
Planning Districts				
George Washington	3.632%	2.305%	1.500%	1.398%
Northern Virginia	2.509%	1.675%	1.066%	1.145%
Rappahannock-Rapidan	1.884%	1.527%	0.909%	0.870%
Northern Shenandoah	1.697%	1.352%	0.778%	0.776%
Thomas Jefferson	1.669%	1.289%	0.823%	0.736%
Richmond Regional (Plan RVA)	1.590%	1.287%	0.786%	0.676%
Central Shenandoah	1.085%	0.804%	0.519%	0.458%
Central Virginia (Region 2000)	0.813%	0.672%	0.479%	0.425%
Middle Peninsula	1.661%	0.525%	0.474%	0.397%
Hampton Roads	1.274%	0.517%	0.378%	0.355%
New River Valley	0.771%	0.471%	0.339%	0.336%
Crater	0.157%	0.374%	0.205%	0.166%
Roanoke Valley-Alleghany	0.388%	0.370%	0.255%	0.246%
Commonwealth Regional	0.762%	0.186%	0.174%	0.186%
Northern Neck	0.920%	0.096%	0.155%	0.042%
Mount Rogers	0.207%	– 0.062%	0.008%	– 0.006%
West Piedmont	– 0.064%	– 0.457%	– 0.212%	– 0.223%
Southside	0.321%	– 0.477%	– 0.234%	– 0.302%
Lenowisco	– 0.352%	– 0.535%	– 0.254%	– 0.226%
Accomack-Northampton	0.559%	– 0.581%	– 0.285%	– 0.291%
Cumberland Plateau	– 0.906%	– 0.751%	– 0.395%	– 0.304%

[a]The VDOT districts and the planning districts are in the order of growth rate in the decade from 2000 to 2020 (column 3, with blue text).

Table 1 shows the VDOT construction districts and the planning districts ordered according to their annualized growth rates in the most recent historical period, the 20 years from 2000 to 2020. During the 20-year period from 2020 to 2040, the total population of the Commonwealth of Virginia is forecast to grow at a rate of 0.688% per year.

One overall pattern evident in Table 1 is that the growth rates for future periods, from 2020 to 2040 and from 2040 to 2060, are closer to zero—that is, smaller in magnitude—than the rates recorded in the most recent historical period from 2000 to 2020. VDOT districts and planning districts that exhibited positive growth rates from 2000 to 2020 are *generally* forecast to have lower positive growth rates in the ensuing periods. In contrast, VDOT districts and planning districts that exhibited negative growth rates from 2000 to 2020 are forecast to contract at slower rates in the ensuing periods.

Table 2 shows the average annualized growth rates of the population aged 65 and older for the Commonwealth, for each VDOT construction district, and for each planning district during the 20-year periods beginning in 1980, 2000, 2020, and 2040. The rates are realized historical rates for the former two periods and Woods & Poole forecast rates for the latter two periods.

Table 2. Annualized Growth Rate of the Population Aged 65 and Older

Location	1980–2000	2000–2020[a]	2020–2040	2040–2060
Virginia Total	2.256%	2.810%	2.018%	0.878%
VDOT Construction Districts				
Northern Virginia	3.720%	4.216%	2.841%	1.204%
Culpeper	2.512%	3.498%	2.116%	0.840%
Fredericksburg	2.679%	3.389%	2.700%	1.219%
Richmond	1.905%	2.857%	1.887%	0.790%
Staunton	1.950%	2.584%	1.846%	0.681%
Hampton Roads	2.517%	2.391%	1.814%	1.143%
Salem	1.742%	2.031%	1.435%	0.170%
Bristol	1.185%	1.585%	0.889%	– 0.032%
Lynchburg	1.348%	1.526%	0.775%	– 0.018%
Planning Districts				
George Washington	3.859%	4.633%	3.594%	1.816%
Northern Virginia	3.720%	4.216%	2.841%	1.204%
Thomas Jefferson	2.531%	3.507%	1.708%	0.718%
Rappahannock-Rapidan	2.314%	3.384%	2.515%	0.887%
Richmond Regional (Plan RVA)	2.033%	3.245%	2.063%	0.878%
Northern Shenandoah	2.173%	3.076%	2.027%	0.697%
Hampton Roads	2.689%	2.486%	1.885%	1.226%
Middle Peninsula	1.752%	2.483%	2.483%	– 0.077%
Central Shenandoah	2.064%	2.407%	1.796%	0.738%
New River Valley	1.706%	2.294%	1.364%	0.426%
Central Virginia (Region 2000)	1.767%	2.148%	1.767%	0.290%
Roanoke Valley-Alleghany	1.423%	1.811%	1.356%	0.337%
Cumberland Plateau	1.247%	1.717%	0.777%	0.039%
Mount Rogers	1.399%	1.647%	1.104%	– 0.239%
Northern Neck	2.003%	1.542%	0.422%	– 1.066%
Southside	1.458%	1.498%	0.612%	– 0.196%
Crater	1.492%	1.492%	1.216%	0.606%
Commonwealth Regional	1.211%	1.479%	1.199%	– 0.086%
Lenowisco	0.688%	1.288%	0.591%	0.038%
West Piedmont	1.599%	1.237%	0.802%	– 0.674%
Accomack-Northampton	0.919%	1.226%	0.332%	– 1.052%

[a]The VDOT districts and the planning districts are in the order of growth rate in the decade from 2000 to 2020 (column 3, with blue text).

Table 2 shows the VDOT construction districts and the planning districts ordered according to their annualized growth rates in the most recent historical period, the 20 years from 2000 to 2020. During the 20-year period from 2020 to 2040, the population aged 65 and older is forecast to grow at a rate of 2.018% per year, a higher rate than the rate of growth of the total population. In the VDOT construction districts and the planning districts, the growth rate of the population aged 65 and older is forecast to be higher than the growth rate of the total population. This pattern presumably reflects increases in longevity from one age cohort to the next and decreases in fertility from one age cohort to the next.

Table 1 shows at least one VDOT construction district and multiple planning districts with negative annualized growth rates of total population in every 20-year period. On the other hand, Table 2 shows no districts with negative annualized growth rates of the population aged 65 and older until 2040 through 2060. This difference between the tables illustrates the extent to which the segment of the population aged 65 and older constitutes an element of persistence and continuity in the population statistics.

The Woods & Poole Time Series Versus the Cooper Center Time Series

As noted previously, the researchers compiled population estimates and forecasts from the Cooper Center and the Woods & Poole datasets because certain clauses in the Code of Virginia prescribe reference to the population estimates that the Cooper Center publishes.

For 2022, the most recent "historical" year in Woods & Poole's population series, Woods & Poole estimated the total population of the Commonwealth of Virginia to be 8,687,361. The Cooper Center estimated the total population of Virginia to be 8,696,955 in 2022. This difference of 9,594 amounts to 0.11% of the population. Table 3 displays the ratio between the Woods & Poole and the Cooper Center estimates in each of Virginia's 21 planning districts for 2010, 2020, and 2030.

Table 3. Ratio of Woods & Poole Estimated Population to Weldon Cooper Center for Public Service Estimated Population

Planning Districts	2010	2020	2030
Lenowisco	0.99818	0.99379	1.12120
Cumberland Plateau	0.99947	0.99921	1.11684
Mount Rogers	1.03648	0.99822	1.05433
New River Valley	1.00051	0.98209	1.03025
Roanoke Valley-Alleghany	0.99879	0.99986	1.02730
Central Shenandoah	0.99782	0.98911	1.01640
Northern Shenandoah Valley	0.99913	0.99976	1.02183
Northern Virginia	1.00175	1.00018	1.00792
Rappahannock-Rapidan	1.00158	1.00015	1.02275
Thomas Jefferson	0.99811	0.98082	1.01491
Central Virginia (Region 2000)	0.99979	0.99378	1.03637
West Piedmont	0.99954	0.99832	1.03988
Southside	0.99689	0.99901	1.08116
Commonwealth Regional	0.99851	0.99455	1.07546
Richmond Regional (Plan RVA)	0.99924	0.99961	0.99888
George Washington	1.00192	1.00086	1.04420
Northern Neck	1.00059	1.00051	1.04041
Middle Peninsula	1.00000	0.99995	1.03977
Crater	0.99768	1.00017	0.99242
Accomack-Northampton	0.99785	0.99813	0.96854
Hampton Roads	1.00024	1.00038	1.01153

Woods & Poole's population estimate differs from the Cooper Center's population estimate by less than 2% in every district in the historical census years 2010 and 2020. In the future census year of 2030, the differences between Woods & Poole's and the Cooper Center's forecast vary by as much as 12%. The Cooper Center's forecast for 2030 is lower in most districts.

Residential Turnover and the Net Rate of Population Change

The rate at which a community's population can grow, or shrink, is related to the rate at which residents move in and out. Even so, a slow, steady population trend at the county or city level may overlie a substantial amount of residential turnover at the neighborhood level (i.e., the census block group). The literature offered three findings:

1. Occupant turnover in rental properties is more than three times as high as it is in owner-occupied housing.
2. The rate of residential turnover is scarcely higher in neighborhoods whose demographic profile is changing than it is in neighborhoods whose demographic profile is not changing.
3. Census block groups that do not gentrify—that is, neighborhoods whose demographic profile remains disadvantaged—tend to gain population more slowly than other block groups, or even to lose population.

A closer look at the first differences in the population numbers—that is to say, at the rate at which population changes year to year in each locality—will give a picture of the range of values that have been seen in Virginia in the past five or more decades. The researchers computed the percentage change in population during the preceding 10-year period for every county and city in Virginia and for every year from 1979 to 2024. The highest percentage change was 119% among all localities in all 10-year periods. The median percentage change was 6.84%. The lowest, the most negative, percentage change was -18.6%. These statistics correspond to annual growth rates of 8.15%, 0.664%, and -2.04%.

Population growth in a particular jurisdiction presumably will be correlated positively with job creation. A cursory comparison of the population and employment historical values and forecasts tabulated in this report confirms this presumption. Population growth is presumably also correlated positively with residential construction. Although residential construction is not the focus of this report, most readers will be aware that Virginia planners pay attention to the number and location of construction building permits in each county and city.

Gentrification, or its opposite, denotes a trend in which the demographic profile of a neighborhood changes over time. Gentrification is studied for several reasons. One reason is to attract economic development and a tax base, and thus, factors that encourage or discourage gentrification are of interest. Another reason is that planners regard involuntary displacement as an undesirable outcome that imposes intrinsic inconvenience on the displaced residents and, therefore, are wary of gentrification. Published studies of gentrification offer three lessons. First, the rate of residential turnover is more than three times as high among renters as it is among homeowners. The turnover rate is an increasing function of the percentage of renters among the households in the neighborhood. Second, turnover happens even in neighborhoods that do not gentrify and is not sensitive to gentrification. Turnover is slightly but perceptibly higher in a neighborhood undergoing gentrification. Third, the more or less stable relocation rate in a low-opportunity, low-demand neighborhood may mean that sometimes a resident moves out and nobody moves in, and the population simply declines.

Cortright (2019), writing about the determinants of involuntary moves, drew on the findings reported by Martin and Beck (2016), with a nod to Freeman (2005). Cortright (2019) observed that the process that social scientists call gentrification has a relatively small effect on a neighborhood's overall turnover and that it is concentrated on renters. In the total sample of the neighborhoods Martin and Beck (2016) studied, the probability that the average renter would have moved after 2 years, voluntarily or not, was 54.0%. In other words, the average renter's tenure in their current abode was 1.7 years. In the subsample of neighborhoods identified as gentrifying, the probability that the average renter would have moved was 55.7%. The difference between the subsample average of 55.7% and the sample average of 54.0% was not statistically significant. The probability that the average renter in the total sample would have moved involuntarily after 2 years was 13.0%. That is, nearly one-fourth of the renters who moved did so involuntarily. The probability that the average renter in the gentrifying subsample would have moved involuntarily was 15.6%. The difference between the subsample average of 15.6% and the sample average of 13.0% was statistically significant. By comparison, the probability that the average homeowner in Martin and Beck's (2016) sample would have moved after 2 years, voluntarily or not, was 16%. In other words, the average homeowner's tenure in their current abode was 4.9 years. This rate scarcely changed in the subsample of gentrifying neighborhoods.

Florida (2017), also commenting on Martin and Beck's (2016) findings, described the differential effect on renters in different terms:

> Controlling for other factors, renters face a 2.6 percent greater probability of being displaced in a gentrifying neighborhood compared to 1.3 percent overall. While this may seem small, it's greater than the difference between residents of subsidized and unsubsidized units and about the same as the difference between a married renter and one who is divorced. (Florida, 2017)

Cortright (2014) made the point that neighborhoods that do not gentrify may also exhibit a kind of instability. Sometimes a resident moves out, nobody moves in, and the population simply declines. Urban census tracts that remained "high poverty" from the 1970 census to the 2010 census lost an average of 40% of their population—an average annual rate of -1.27%.

The Woods & Poole package contains historical county- and city-level data for Virginia, covering the period from 1969 to 2024. Martin and Beck's (2016) dataset contained census tract-level data from around the United States covering the period from 1987 through 2009. These datasets are not quite apples to apples. Nonetheless, a comparison may be instructive. The median percentage change during a 10-year period, which the researchers found in Woods & Poole's Virginia population data, was 6.84%, an annual rate of 0.664%. The 2-year rates of turnover seen in Martin and Beck's (2016) dataset—54% for renters and 16% for homeowners—imply annual turnover rates of 32.2% for renters and 8.3% for homeowners.

Employment

VTRC has collaborated with OIPI for several consecutive iterations of the VTrans exercise to compile three VTrans trend trackers related to employment. Macrotrend 7, Growth of the Professional Services Industry, recognizes two trend trackers, which are the Share of the Professional Services Industry in total employment and the Number of STEM Jobs, or jobs that apply science, technology, engineering, and mathematics. Employment in the Woods & Poole Professional and Technical Services category is taken to be a tolerable fit for each of these definitions. Macrotrend 10, Population and Employment Shift, recognizes four trend trackers. The third of these trackers is Employment, taken to mean total employment in each county and city.

In fact, a fourth VTrans trend tracker pertains to employment. Macrotrend 5, Growth in E-commerce, recognizes four trend trackers, including the Number of Jobs in Goods Movement-Dependent Industries. This study took some preliminary steps to develop a statistic to match this definition.

To the employment compilations, this study added a brief literature review that addresses the potential effects of AI adoption on the workplace and the job market and a brief review of the institutional framework that determines how the expectations of these effects are incorporated into employment forecasts.

The Rate of Total Employment Change

Employment growth is a direct driver of the growth of commuter travel demand and an indirect driver of the growth of freight transport demand. For a transport agency that cooperates with an economic development agency, employment growth is also a measure of success.

Table 4 shows the average annualized growth rates of total employment for the Commonwealth, for each VDOT construction district, and for each planning district during the 20-year periods beginning in 1980, 2000, 2020, and 2040. These rates are realized historical rates for the former two periods and Woods & Poole forecast rates for the latter two periods.

Table 4 shows the VDOT construction districts and the planning districts ordered according to their annualized growth rates in the most recent historical period, the 20 years from 2000 to 2020. During the 20-year period from 2020 to 2040, total employment in the Commonwealth of Virginia is forecast to grow at a rate of 1.547% per year. The reader will note that this growth rate is higher than the forecasted rate of population growth of 0.688% per year (Table 1). As these two rates, taken together, imply that employment will grow about 0.859% per year faster than population, they imply a forecast that labor force participation will increase during this period.

One pattern evident in Table 4 is that the growth rate for the period from 2020 to 2040 is forecast to exceed substantially the growth rate from 2000 to 2020 in every planning district. This pattern may reflect a prediction from Woods & Poole's economic model that employment will rebound from the negative shocks of the COVID-19 lockdown in 2020. The growth rates forecast for the period from 2040 to 2060 are less optimistic, yet still positive in every planning district.

Table 4. Annualized Growth Rate of Total Employment

Location	1980–2000	2000–2020[a]	2020–2040	2040–2060
Virginia Total	2.291%	0.864%	1.547%	1.070%
VDOT Construction Districts				
Fredericksburg	3.701%	1.739%	2.055%	1.878%
Northern Virginia	3.793%	1.528%	2.092%	1.396%
Culpeper	2.624%	1.318%	1.575%	1.062%
Richmond	1.855%	1.008%	1.441%	0.909%
Staunton	1.996%	0.657%	1.241%	0.830%
Hampton Roads	1.782%	0.390%	1.105%	0.683%
Salem	1.437%	– 0.133%	0.868%	0.508%
Lynchburg	0.894%	– 0.278%	0.807%	0.607%
Bristol	0.636%	– 0.646%	0.471%	0.368%
Planning Districts				
George Washington	5.077%	2.261%	2.412%	2.146%
Northern Virginia	3.793%	1.528%	2.092%	1.396%
Rappahannock-Rapidan	2.607%	1.337%	1.288%	0.965%
Thomas Jefferson	2.584%	1.300%	1.696%	1.101%
Richmond Regional (Plan RVA)	2.119%	1.179%	1.540%	0.966%
Northern Shenandoah	2.550%	1.020%	1.202%	0.905%
Central Shenandoah	1.825%	0.541%	1.325%	0.805%
Middle Peninsula	2.149%	0.410%	0.848%	0.581%
Hampton Roads	1.836%	0.405%	1.130%	0.690%
Northern Neck	0.832%	0.369%	0.574%	0.425%
Crater	0.711%	0.291%	0.763%	0.492%
New River Valley	1.550%	0.242%	1.039%	0.499%
Central Virginia (Region 2000)	1.494%	0.174%	1.028%	0.830%
Accomack-Northampton	0.507%	0.142%	0.384%	0.401%
Roanoke Valley-Alleghany	1.539%	– 0.112%	0.784%	0.459%
Commonwealth Regional	1.012%	– 0.188%	0.848%	0.772%
Lenowisco	0.421%	– 0.619%	0.421%	0.638%
Mount Rogers	1.250%	– 0.662%	0.558%	0.290%
Cumberland Plateau	– 0.137%	– 0.950%	0.310%	0.327%
Southside	0.615%	– 1.002%	0.426%	0.244%
West Piedmont	0.194%	– 1.114%	0.471%	0.161%

[a]The VDOT districts and the planning districts are in the order of growth rate in the decade from 2000 to 2020 (column 3, with blue text).

Growth of Employment in Professional and Technical Services

Table 5 shows the average annualized growth rates of employment in the professional and technical services sector for the Commonwealth, for each VDOT construction district, and for each planning district during the 20-year periods beginning in 1980, 2000, 2020, and 2040. These rates are realized historical rates for the former two periods and Woods & Poole forecast rates for the latter two periods.

Table 5. Annualized Growth Rate of Employment in Professional and Technical Services

Location	1980–2000	2000–2020[a]	2020–2040	2040–2060
Virginia Total	5.46%	2.28%	2.48%	1.83%
VDOT Construction Districts				
Fredericksburg	6.08%	2.98%	1.15%	1.38%
Culpeper	4.77%	2.66%	2.51%	2.03%
Northern Virginia	6.42%	2.48%	2.70%	2.77%
Richmond	3.94%	2.48%	1.46%	1.00%
Lynchburg	3.28%	2.43%	1.23%	0.82%
Staunton	4.20%	2.37%	2.76%	1.93%
Hampton Roads	4.54%	1.44%	2.49%	1.93%
Salem	3.86%	0.88%	1.36%	0.97%
Bristol	2.94%	0.80%	1.97%	1.69%
Planning Districts				
George Washington	7.098%	3.332%	2.899%	2.960%
Northern Shenandoah	4.669%	2.976%	1.695%	1.585%
Thomas Jefferson	4.967%	2.753%	2.761%	2.268%
Accomack-Northampton	3.234%	2.616%	2.064%	1.581%
Rappahannock-Rapidan	4.287%	2.539%	1.832%	1.268%
Central Virginia (Region 2000)	4.542%	2.532%	1.371%	1.009%
Richmond Regional (Plan RVA)	3.973%	2.498%	2.498%	1.954%
Northern Virginia	6.422%	2.479%	2.756%	1.925%
Commonwealth Regional	3.047%	2.153%	1.922%	0.557%
Crater	3.319%	2.151%	1.895%	1.776%
Northern Neck	2.607%	1.995%	1.157%	1.057%
Central Shenandoah	3.970%	1.853%	2.253%	1.800%
New River Valley	4.103%	1.718%	1.377%	0.680%
Southside	3.192%	1.562%	1.562%	1.439%
Cumberland Plateau	2.346%	1.469%	2.047%	2.650%
Hampton Roads	4.586%	1.407%	1.441%	0.971%
Mount Rogers	3.456%	1.004%	0.611%	0.238%
Middle Peninsula	3.806%	0.830%	1.443%	0.709%
Roanoke Valley-Alleghany	3.547%	0.643%	0.643%	1.309%
West Piedmont	2.797%	-0.025%	1.270%	0.648%
Lenowisco	2.899%	-0.336%	0.636%	0.506%

[a]The VDOT districts and the planning districts are in the order of growth rate in the decade from 2000 to 2020 (column 3, with blue text).

Table 5 shows the VDOT construction districts and the planning districts ordered according to their annualized growth rates in the most recent historical period, the 20 years from 2000 to 2020. During the 20-year period from 2020 to 2040, employment in the professional and technical services sector is forecast to grow at a rate of 2.28% per year, a higher rate than the growth rate forecast for total employment. In the individual VDOT construction districts and the individual planning districts, the employment growth rate in the professional and technical services sector is forecast to be higher than the total employment growth rate.

The Number of Jobs in Industries Dependent on Goods Movement

In The VTrans framework, macrotrend 5, Growth in E-commerce, recognizes four trend trackers. The fourth of these trend trackers is the Number of Jobs in Goods Movement-Dependent Industries (OIPI, 2025a).

Four Feasible Definitions of Goods Movement Dependence

The Bureau of Economic Analysis (BEA) of the U.S. Department of Commerce periodically updates and publishes The Use of Commodities by Industries—Sector table. This table tallies the number of dollars' worth of intermediate goods and services that the companies in one sector of the American economy—construction, for example—purchase during a given year from the companies in each sector of the American economy, including their own sector—agriculture, forestry, fishing, and hunting; mining; utilities; construction; manufacturing; wholesale trade; retail trade; and so forth. One column of the table shows how many dollars of the sector's total output went to pay for purchases from other companies in each sector and how many dollars of output remained to be allocated to compensation of employees, taxes, profit, and so on (BEA, 2024). The economic sector of interest to the researchers was transportation and warehousing, or sector 48TW in BEA's classification system.

The researchers consulted the 2023 edition of the aforementioned BEA table. They then tabulated each sector's intermediate goods and services purchases from sector 48TW separately as a fraction of the sector's Total Intermediate goods and services purchases (row T005). They also tabulated separately each sector's intermediate goods and services purchases from sector 48TW as a fraction of the Total Intermediate goods and services purchases from sector 48TW.

By either of these two tabulations, three economic sectors stood out, exhibiting percentages of purchases from the transportation and warehousing sector well above the overall average and well above the fourth highest purchasing sector. Each of these three sectors—wholesale trade, retail trade, and transportation and warehousing—devoted more than 10% of its total expenditures on intermediate goods and services to purchases from the transportation and warehousing sector. Each of these three sectors accounted for more than 14% of the total intermediate goods and services purchases from the transportation and warehousing sector. When the researchers tabulated each sector's purchases from sector 48TW as a fraction of the sector's Value Added (basic prices) (row VABAS), and as a fraction of the sector's Total Industry Output (basic prices), the same three economic sectors led the pack. It is worth noting that Woods & Poole's files VA039, VA040, and VA041 contain employment in these three sectors.

The same four tabulations revealed a middle group consisting of seven or eight sectors, depending on the fraction computed, and a lowest group consisting of four or five sectors. Table 6 shows the tabulations described previously.

As noted, the same top three sectors emerge in every one of the four measures tested. By the three measures that calculate each sector's intermediate purchases from sector 48TW as a fraction of that sector's own totals, the utilities sector always comes in fourth place, and the government sector always comes in fifth place. By the measure that calculates each sector's intermediate purchases from sector 48TW as a fraction of total intermediate purchases from sector 48TW, however, the government sector comes in fourth place, the professional and business services sector comes in fifth, and the finance, insurance, real estate, rental, and leasing sector comes in a close sixth.

Table 6. Four Measures of the Degree of Dependence on Goods Movement in 2023[a]

Sector	As Fraction of Sector's Own Total Interm. Purchases	As Fraction of Sector's Own Value Added	As Fraction of Sector's Own Total Output	As Fraction of all Interm. Purchases from Sector 48TW
Agriculture, Forestry, Fishing, and Hunting	0.27%	0.33%	0.15%	0.12%
Mining	0.38%	0.30%	0.17%	0.15%
Utilities	4.75%	2.24%	1.52%	1.20%
Construction	0.13%	0.12%	0.06%	0.18%
Manufacturing	0.75%	1.17%	0.46%	4.28%
Wholesale Trade[b]	11.50%	10.02%	5.36%	17.74%
Retail Trade	10.95%	7.47%	4.44%	14.23%
Transportation and Warehousing	26.05%	23.01%	12.22%	27.30%
Information	1.86%	1.35%	0.78%	2.51%
Finance, Insurance, Real Estate, Rental, and Leasing	1.79%	1.09%	0.68%	8.19%
Professional and Business Services	3.28%	1.81%	1.17%	8.37%
Educational Services, Healthcare, and Social Assistance	2.34%	1.41%	0.88%	4.29%
Arts, Entertainment, Recreation, Accommodation, and Food Services	1.66%	1.51%	0.79%	2.11%
Other Services, except Government	0.84%	0.63%	0.36%	0.46%
Government	3.43%	2.17%	1.33%	8.88%
All sectors average	3.73%	2.88%	1.62%	

48TW = transportation and warehousing sector; Interm. = intermediate. [a] Based on each sector's purchase of intermediate goods and services from sector 48TW. [b]The three rows with blue text represent the sectors with the highest share of intermediate goods and services purchases from sector 48TW.

Goods Movement-Dependent Employment as a Share of Total Employment

The researchers aggregated employment in the three most goods movement-dependent sectors identified previously. Table 7 shows the tally for these three sectors in 1980, 2000, and 2020 and the forecast for 2040 and 2060. The table also shows the average growth rate, historical or forecast, for each 20-year period and the share of these three sectors in total employment in Virginia.

Table 7. Aggregate Employment (in 1000s) in the Three Most Goods Movement-Dependent Sectors

Variable	1980	2000	2020	2040	2060
	454.8570	745.7710	847.2310	1001.5210	1089.2790
20-year average growth rate	N/A	2.50%	0.64%	0.84%	0.42%
Aggregate employment as a share of total employment	0.1627	0.1695	0.1622	0.1410	0.1240

The historical statistics show a declining growth rate for employment in these three sectors, and Woods & Poole forecast that the growth rate will continue to decline. Comparing the growth rates in Table 7 with those in Table 4, the reader will notice that, starting in 2000, the historical and forecast growth rates for these three sectors are less than the historical and forecast growth rates for total employment in Virginia. This being the case, it is no surprise that Table 7 also shows the share of employment in these three sectors declining from 2000 onward.

Caveats and Qualifications

The limited analysis in the previous section leaves numerous questions unanswered. At least two additional remarks deserve mention. First, the increasing popularity of online shopping may not manifest as an increase in employment within the goods movement-dependent industries as a group. The shift toward online shopping may manifest as a shift in employment numbers between the sectors in this group. The shift may manifest as an increase in final consumer purchases of goods and services from the transportation and warehousing sector, a category of purchases that the analysis ignored.

Second, the computations rely on publicly available economic data. Of course, BEA's industrial classifications were not defined to identify goods movement dependence. A thorough search specifically for goods movement-dependent enterprises might reveal that each economic sector contains a subset of enterprises that are more particularly dependent on goods movement than the sector as a whole.

Employment Projections Since the Emergence of Large Language Models

Much journalism has been devoted recently to the potential ramifications of adopting generative AI, such as LLMs, on the skills required in the workplace, the distribution of tasks and responsibilities, and the number of jobs. A recent story from the news media ran with the headline "Amazon to Lay Off Up to 30,000" and quoted a memorandum from the company's chief executive officer: "As we roll out more Generative AI and agents, it should change the way our work is done. It's hard to know exactly where this nets out over time, but in the next few years, we expect that this will reduce our total corporate workforce." (McLain, 2025.)

One question of interest is how analysts incorporate the effects of generative AI into employment forecasts. Because BLS is the authoritative source of long-term national employment projections, the research team examined how BLS takes generative AI into account in these forecasts, considering the following four dimensions:

- BLS projection principles.
- BLS qualitative adjustments.
- Consideration of AI as an exogenous factor.
- Lessons learned from previous forecasts.

Bureau of Labor Statistics Projection Principles

BLS projections incorporate extensive quantitative analysis to initiate employment projections, moving logically from constrained estimates of Gross Domestic Product to components of final demand to more detailed projections of production in the form of goods and services and then to the employment necessary to produce the Gross Domestic Product model solution (BLS, 2024a, 2024b). The BLS approach adheres to the following guiding principles learned from decades of projections (Machovec et al., 2025):

- Historical data will register structural changes (e.g., technology) in the labor market.

- Historically, the effects on employment have manifested gradually.
- Labor displacement, when it has occurred, has taken longer than “technologists” anticipated it would.
- Occupations affected by technology have often still grown absolutely larger.
- Uncertainty regarding the effects of breakthrough technology is substantial.

This is not to say that projections are simple linear extrapolations of past overall employment or occupational employment growth. Rather, BLS employment projections identify and follow broad data trends for the purpose of cross-walking them to employment trends. When data trends indicate that an emerging technology has reached maturation and its full diffusion into the economy, its effects will be expected to diminish during the projection. If data trends indicate that a new technology is still being adopted—perhaps by co-inventing its use applications, as may be the case with generative AI (Eloundou et al., 2023)—its effects on the economy are expected to continue according to BLS projection principles. A substantial challenge lies in determining whether the evidence sufficiently supports building the anticipated effects of an emerging technology on employment into the decadal projection (Machovec et al., 2025).

Two examples illustrate the BLS methodology in adjusting a projection. In the early 2000s, digital cameras were rapidly displacing film cameras in the general population. Given that digital cameras improved existing technology and that the business and consumer markets were readily accessible, BLS broke from the historical trend growth and projected a sharp decline in the occupation of photographic process workers between 2004 and 2014 that turned out to be accurate but understated—23.5% projected versus 66.6% actual in 2014 (Machovec et al., 2025). The emergence of autonomous vehicles, however, was insufficient to cause BLS to adjust its model projections for truck driving occupations in the 2010s because of the inherent friction of adoption in the face of regulatory and public safety concerns.

In general, technologies that introduce incremental changes to business practices are more readily incorporated into BLS projections than breakthrough technologies because the former can use historical trends as a real frame of reference.

Bureau of Labor Statistics Qualitative Adjustments

BLS subsequently revealed the qualitative judgments it used in the 2023–2033 projections for occupations implicated in Felten et al.’s (2023) findings (Machovec et al., 2025; BLS, 2025). BLS determines whether AI would facilitate a productivity change in an occupation, inferring from a positive productivity change whether, on net, human jobs will decline. This net negative impact was expected to be the result by 2033 for claims adjusters, examiners, and investigators; hydrologists; paralegals and legal assistants in both private and public sectors; tutors; technical writers; broadcast technicians; sound engineering technicians; lighting technicians; radiologists; medical transcriptionists; amusement and recreation attendants; insurance sales agents; financial services sales agents; travel agents; and sales representatives of some services, including those in wholesale and manufacturing and of technical and scientific products. On the other hand, software developers, computer network architects, information security analysts, and training and development specialists were expected to experience higher net demand, even if AI were to enhance their productivity (BLS, 2025).

BLS projects decadal employment trends in “shock”-free scenarios. Other products of the U.S. Department of Labor include databases that track occupational characteristics (e.g., basic skills required, hours, and wages) using methods that rely on voluntary worker surveys and on the extent and quality of participation in those surveys). The data are collected and assembled to meet the needs of job-seekers. With no other avenue for comparing real-world occupational skill sets with breakthrough technology, many researchers have turned to the same data during the past decade to measure the competition that AI poses for U.S. jobs (O*NET OnLine, 2025).

To impose a firmer temporal dimension on the speculation, Handel (2022) juxtaposed 10 occupations (taken as wholes rather than task sets), which were identified in recent research as adaptive to emerging AI and robotics, against 17 occupations that earlier computerization innovation was believed to have affected and that AI might further affect: “At the most basic level, concerns regarding automation are supported if [the 10] occupations are projected to decline sharply in the 2019–2029 period and, secondarily, if they also shrank in the 2008–2018 period with the birth of the modern AI industry.”

This simple panel comparison implicitly reflects the declining growth in the labor force during the 1999–2019 period. This factor would strongly inhibit job creation overall regardless of technological innovations and, by so doing, would obscure their effects. Forced by the demographic constraint to look differently at the data for a quality control check, Handel (2022) noted that the 10 occupations of the AI-susceptible category constitute a larger *share* of the total labor force in the 2018 actuals than in 2008. Thus, the decadal *growth* from 2008 to 2018 in the *share* of total employment in occupations that should have declined if sensitive to breakthrough technology supports the credibility of the BLS projection method. The BLS projection gives even a slightly larger share to AI-susceptible occupations during 2019 through 2029, although some individual occupations in the group of 10 will grow more slowly than they had from 2008 to 2018 and two will decline.

For the 17 occupations that earlier computerization likely affected, BLS projected an employment share in 2018 (11.5%) that was very close to the actual 2018 share (11.4%), yet again supporting the BLS projection methodology (Handel, 2022). In 2029, total employment in those occupations is projected to decline but only slightly, and no evidence suggests sudden job losses coinciding with the emergence of recent technology in any of the seven occupations in actuals or projections, defying the sweeping losses forewarned in recent research. It is also important to note that, “In general, most occupations are small, few decline by 30% or more over 10 years, and those that do so account for a small share of the total number of jobs” (Handel, 2022), declining gradually rather than cataclysmically.

To summarize, technology is constrained in how sharply it affects employment because many diverse jobs exist within occupations as BLS measures them, and within those jobs the tasks are diverse, all with varying levels of exposure to technology. As tasks are automated, it is unclear a priori how any specific job will be reformed and equally unclear that the job will be eliminated. Growth in product demand can also lead to increased technology-augmented employment. At least, this is patently clear for the AI-creating and -related industries themselves (Handel, 2022).

Because VDOT continues to use proprietary industry employment projections based on North American Industry Classification System (NAICS) codes (U.S. Census Bureau, 2025), it is key to remember that NAICS industry codes hold very different occupations with different vulnerabilities even to current AI technologies. For example, establishments in NAICS Sector 54—professional, scientific, and technical services—include several occupations that require advanced training and expertise, such as exist in two industries that are among the top 10 industries for projected wage and salary employment *growth*: computer systems design and related services and management, scientific, and technical consulting services. On the other hand, establishments in Sector 54 also include occupations that AI technologies are likely to challenge: translation and interpretation services, graphic designers, and legal secretaries and administrative assistants (Colato et al., 2024).

Consideration of Artificial Intelligence as an Exogenous Factor

BLS begins its employment projection computations by constraining estimates of the initial size and subsequent change in the labor force during the following decade, then introducing considerations related to exogenous factors, such as AI. For example, the aging U.S. population is a continuing root cause of slower population and labor force growth during the 2023–2033 projection and, via falling consumer demand, a cause of lower Gross Domestic Product growth as well (Dubina, 2024). BLS projects that the labor force participation of the 75-and-older age group will grow the most of all age groups 55 and older, rising from a share of 8.3% in 2023 to 10.1% in 2033, or nearly 22%. Because the 75-and-older age group consists of Baby Boomers, they are also more numerous than the younger groups 55 and older, and their increased participation in the labor market could be consequential for consumer applications of AI (e.g., wearable health monitors or emergency devices, or even autonomous vehicles).

By contrast, the population aged 16 to 24 is projected to decline because of falling fertility rates since 2010, and their declining trend in labor force participation is expected to continue, for reasons explored in Abraham and Kearney (2019). Of the prime-age workforce, aged 25 to 54, BLS expects long-term trends to continue, with male participation falling from 89.1% to 87.4% and female participation rising marginally from 77.4% to 77.8% (Dubina, 2024). These broad trends run parallel to the trend in the mining industry to apply labor-saving AI technology (Jackson, 2023) and suggest that BLS projections may anticipate labor-saving technology being pursued in other demanding male-dominated fields during the 2023–2033 projection, for both demographic and policy reasons—for example, in the case of mining, the policy being federal incentives for domestically sourced carbon ore, rare earths and critical minerals (U.S. Department of Energy, 2025).

Policy heavily influences BLS projections, although policies change from decade to decade. To emphasize the importance of the background policy environment, consider the 2023–2033 projection of a 60.1% increase in wind turbine service technicians and a 48% increase in solar photovoltaic installers. These projections surely reflect the national energy transition policies implemented in 2021-2022 and conveyed for the purpose of uninterrupted continuity to a successive generation of similar policy instruments to become effective in 2025 (Volcovici, 2024). Although new policies that have been implemented since the federal elections of 2024 and going forward will inevitably affect actuals for these occupations in 2033 as well as projections made in 2025, the effect at the occupational level may be unchanged. That is, demand for the occupations may come from continuing state and federal government policy support for AI technology that, at present, may be reliably expected to require a broad-based energy supply (Chu and Hurst, 2025). Furthermore, the national interest in AI technology will almost certainly continue to support relatively high job growth for information security analysts, an occupation projected in 2022 to grow at 32.7% during the decade (Colato et al., 2024).

According to the standard BLS full-employment occupational projection for 2033, two industries are expected to account for most employment growth. First, the healthcare and social assistance industry, NAICS Sector 62, is expected to add approximately 2.5 million jobs. One contributing factor is that because women tend to live longer in worse health compared with men of the same age, and they tend to use long-term facilities more than home healthcare compared with men (Kallestrup-Lamb et al., 2024), women will differentially contribute in older ages to demand for health industry employment. Second, the professional, scientific, and technical services industry, NAICS Sector 54, is projected to add slightly more than 1 million new jobs (Colato et al., 2024). Many of the new jobs are related directly to AI adoption; at the same time they continue a long-term industry trend of job growth for other technology-related reasons. For all occupations, however, demographic trends will necessarily be a top factor influencing BLS employment projections that incorporate AI diffusion.

Lessons Learned from Previous Forecasts

Alpert and Auyer (2003) performed an ex-post evaluation of the BLS 1988 employment projection for 2000 against actual levels in 2000, finding that two of the nine major occupational groups accounted for the largest numerical errors. In addition, 10 detailed occupations of the 338 examined showed projection discrepancies from the actuals in excess of 300,000 jobs. Six of these—two overprojections and four underprojections—had absolute percent errors, between the projected and actual values, below the average of about 23% for the overall projection, implying that the BLS projections for those six occupations were relatively accurate, or at least not distinctly inaccurate. Table 8 displays these patterns.

Table 8. Actual 2000 Employment Totals, by Sector, Versus 1988 Projections of the 2000 Totals

Job Type[a]	Absolute % Error
Retail salespersons (overprojection)	8.1%
Word processors, typists (overprojection)	91.7%
Secretaries except legal, medical (overprojection)	15.6%
Truck drivers, light and heavy	9.9%
Blue-collar worker supervisors	13.7%
Office and administrative support supervisors and managers	21.6%
Shipping, receiving, traffic clerks	42.4%
Teacher assistants	34.8%
Hand packagers and packers	45.1%
Cashiers	20.5%

[a]All categories were underprojections except for the first three.

Overall, the aggressive incursion of computer technology by 2000 appears to have been unanticipated for word processors and typists, given the absolute percent error of 91.7%. Alpert and Auyer (2003) noted that only six of the 20 detailed occupations that BLS projected in 1988 would grow the fastest actually accomplished this by 2000. Still, projection error does not account for all projection "misses." The dynamic nature of BLS-identified occupations at the time of any projection caused an underprojection in 1988 of computer-*related* employment in 2000 of *nearly a million jobs*. BLS can only project the occupations that exist in the projection year, not the occupations that might exist in the target year. In 1988 only one occupation, systems analysts, existed in the computer-related family, but nearly one million jobs were added in three new computer-related occupations that came into existence in 1998, just in time to be counted in the 2000 actuals (Alpert and Auyer, 2003).

Summary of the Effect of Large Language Models on Employment Projections

In summary, after fielding technology challenges for decades, BLS takes a long and gradual view of job evolution for three reasons. First, its signature product is a long-term *projection* rather than a short-term *forecast*. Second, many parameters that profoundly influence employment are also long-term forces, such as population growth, labor force growth, population aging, labor force participation, and others. Third, its projections intentionally do not speculate on the effects of exogenous shocks such as sudden war, deadly pandemics, or technology that is assumed to diffuse more rapidly than in the historical record. As analytical methods mature with respect to the effects of AI technologies on employment, research findings are also becoming more nuanced with respect to economic benefits than they were 10 to 15 years ago (Acemoglu, 2024; Finze et al., 2024; Hampole et al., 2025), and therefore they are more instructive, for both BLS and for proprietary analysts, in understanding barriers to technology diffusion. In any case, proprietary publishers of macroeconomic projections are likely to continue to conform to BLS practices because of the notoriety that would ensue from a wildly dissonant projection relative to the BLS product, even given typical BLS error rates.

Based on Lightcast data, the Stanford Institute for Human-Centered AI's *Artificial Intelligence Index Report* by Gil and Perrault (2025) states that U.S. job postings requesting AI skills in 2024 occurred most often in the information (Sector 51, 9.33%), the professional, technical, and scientific services (Sector 54, 5.25%), the finance and insurance (Sector 52, 3.76%), and the manufacturing (Sectors 31 to 33, 3.75%) NAICS sectors, all growing by double digits since 2023. Public administration had fewer requests for AI skills in job listings in 2024 than in 2023. Ten other two-digit level NAICS industries had rates of 2.15% or lower (Gil and Perrault, 2025). Even among the top industries listed, AI skills were listed in a small minority of job descriptions, although every industry has shown double-digit growth in job listings including AI skills since 2023.

The BLS method of marginal adjustments in occupational projections, which responds predominantly to demography and national policy, therefore seems justified. Nevertheless, BLS methods coexist necessarily with powerful voices and forces predicting sweeping job losses across the globe in the coming years, albeit possibly in the hopes of soon recouping prodigious investments made in technology (Catacora, 2024).

Personal Income

One VTrans trend tracker pertains to income in Virginia. Macrotrend 10, Population and Employment Shift, recognizes four trend trackers. The fourth of these trackers is Income. Bhairavabhatla et al. (2020), compiling trend trackers for a previous update of VTrans, compiled the Household Income time series included in the 2018 Woods & Poole dataset and conducted some analysis of the trends in that series. To the current research team's best knowledge, this time series did not become one of the trend trackers that VTRC compiled and formatted routinely for OIPI.

The Woods & Poole dataset, which OIPI purchased for the most recent iterations of the VTrans updates, includes both the Household Income time series mentioned previously and a Personal Income time series. Either income series may serve as a meaningful indicator of a locality's revenue base. Household income may be a meaningful indicator of a locality's consumption behavior, such as vehicle ownership. Personal income per capita may be a meaningful indicator of the locality's demographic profile. This task, Task 1, examined the Personal Income time series. Task 3 experimented with both the Personal Income and the Household Income time series.

To the personal income compilations, this study added a brief review of the literature that concerns demographic change over time, in the form of gentrification or in other forms, and a brief discussion of the implications of demographic change for transport planners charged with considering the effect of a transport investment on a particular demographic subset of the population.

Growth of Personal Income

Table 9 shows the average annualized growth rates of total personal income for the Commonwealth, for each VDOT construction district, and for each planning district, during the 20-year periods beginning in 1980, 2000, 2020, and 2040. These rates are realized historical rates for the former two periods and Woods & Poole forecast rates for the latter two periods.

Table 9 shows the VDOT construction districts and the planning districts ordered according to their annualized growth rates in the most recent historical period, the 20 years from 2000 to 2020, in the column with blue text. During the 20-year period from 2020 to 2040 the total personal income of the Commonwealth of Virginia is forecast to grow at a rate of 2.212% per year. This rate of growth is higher than the forecasted rate of population growth of 0.688% per year (Table 1). These two, taken together, imply a forecast that per capita income will increase at the rate of about 1.524% per year. This pattern is consistent with the pattern that Bhairvabhatla et al. (2020) found when examining the household income forecasts in the 2018 edition of the Woods & Poole dataset.

Table 9. Annualized Growth Rate of Total Personal Income

Location	1980–2000	2000–2020[a]	2020–2040	2040–2060
Virginia Total	3.913%	2.427%	2.212%	2.004%
VDOT Construction Districts				
Fredericksburg	5.106%	3.448%	2.738%	2.803%
Culpeper	4.977%	3.185%	2.191%	1.877%
Northern Virginia	4.971%	2.675%	2.691%	2.293%
Richmond	3.682%	2.607%	1.976%	1.773%
Staunton	3.687%	2.581%	1.914%	1.698%
Hampton Roads	3.143%	1.895%	1.680%	1.548%
Salem	3.003%	1.674%	1.501%	1.427%
Lynchburg	2.395%	1.459%	1.338%	1.365%
Bristol	1.358%	1.073%	1.141%	1.194%
Planning Districts				
George Washington	5.964%	3.997%	3.142%	3.101%
Thomas Jefferson	4.989%	3.209%	2.281%	1.827%
Rappahannock-Rapidan	4.840%	3.078%	1.998%	1.926%
Northern Shenandoah Valley	4.307%	3.074%	1.917%	1.825%
Richmond Regional (PlanRVA)	3.927%	2.819%	2.055%	1.823%
Northern Virginia	4.971%	2.675%	2.691%	2.293%
Accomack-Northampton	2.856%	2.427%	0.690%	1.086%
Central Shenandoah	3.442%	2.302%	1.977%	1.614%
Middle Peninsula	4.029%	2.156%	1.448%	1.430%
Northern Neck	3.211%	2.097%	1.187%	1.248%
New River Valley	2.998%	2.091%	1.546%	1.383%
Hampton Roads	3.163%	1.892%	1.712%	1.559%
Commonwealth Regional	2.941%	1.721%	1.442%	1.447%
Central Virginia (Region 2000)	3.269%	1.715%	1.647%	1.635%
Roanoke Valley-Alleghany	2.842%	1.569%	1.452%	1.385%
Mount Rogers	2.617%	1.313%	1.264%	1.245%
Crater	2.330%	1.174%	1.317%	1.401%
Southside	2.507%	1.149%	1.190%	1.182%
Lenowisco	1.035%	0.976%	1.132%	1.240%
West Piedmont	1.824%	0.895%	1.000%	0.989%
Cumberland Plateau	0.219%	0.857%	0.908%	1.088%

[a]The VDOT districts and the planning districts are in the order of growth rate in the decades from 2000 to 2020 (column 3, with blue text).

The Trend of Personal Income per Capita

The researchers divided the historical and forecast personal income estimates in the Woods & Poole dataset by the population of each planning district to obtain the personal income per capita in each district. Figures 1 through 4 show shaded maps of personal income per capita in each planning district, as recorded in 2000 and 2020 and as forecasted for 2030 and 2050.

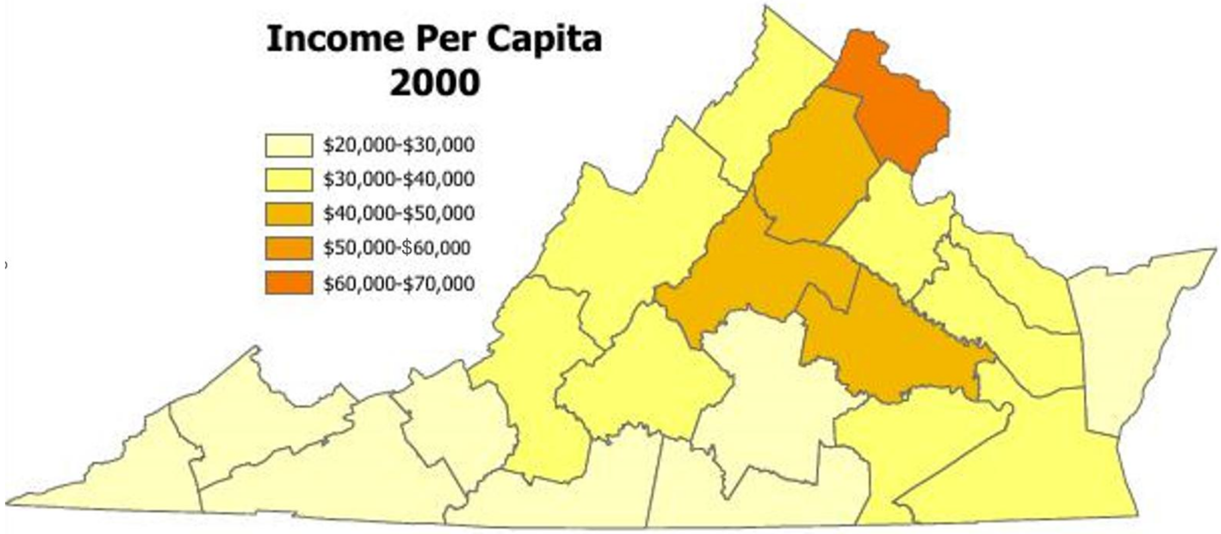

Figure 1. Personal Income per Capita in Each Planning District, 2000. A district whose income per capita equaled *exactly* $30,000 would be assigned to the "$30,000–$40,000" bracket and so on.

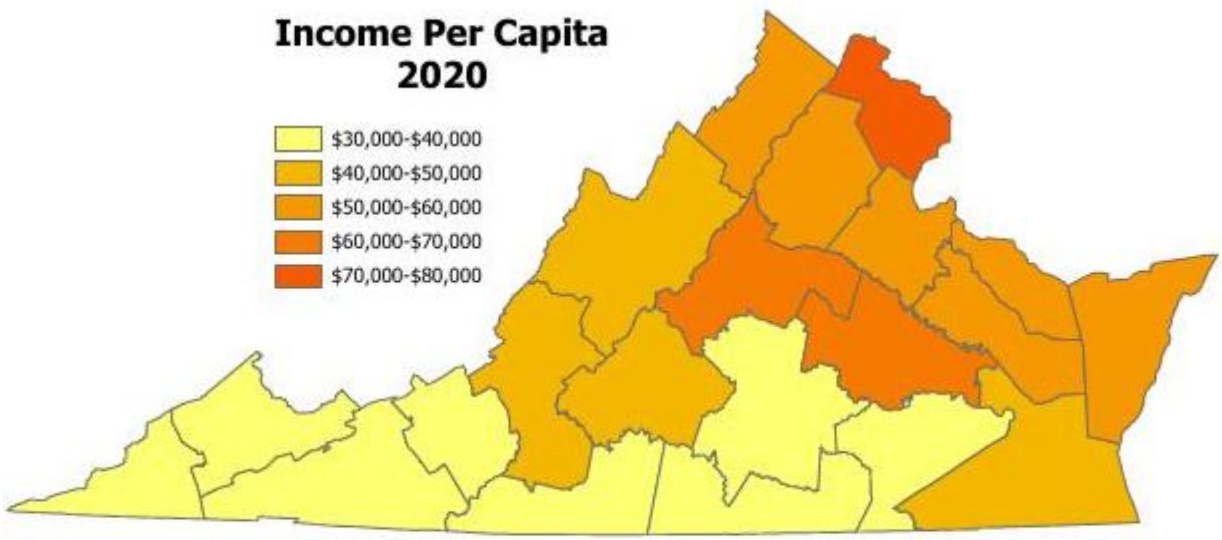

Figure 2. Personal Income per Capita in Each Planning District, 2020. A district whose income per capita equaled *exactly* $40,000 would be assigned to the "$30,000–$40,000" bracket and so on.

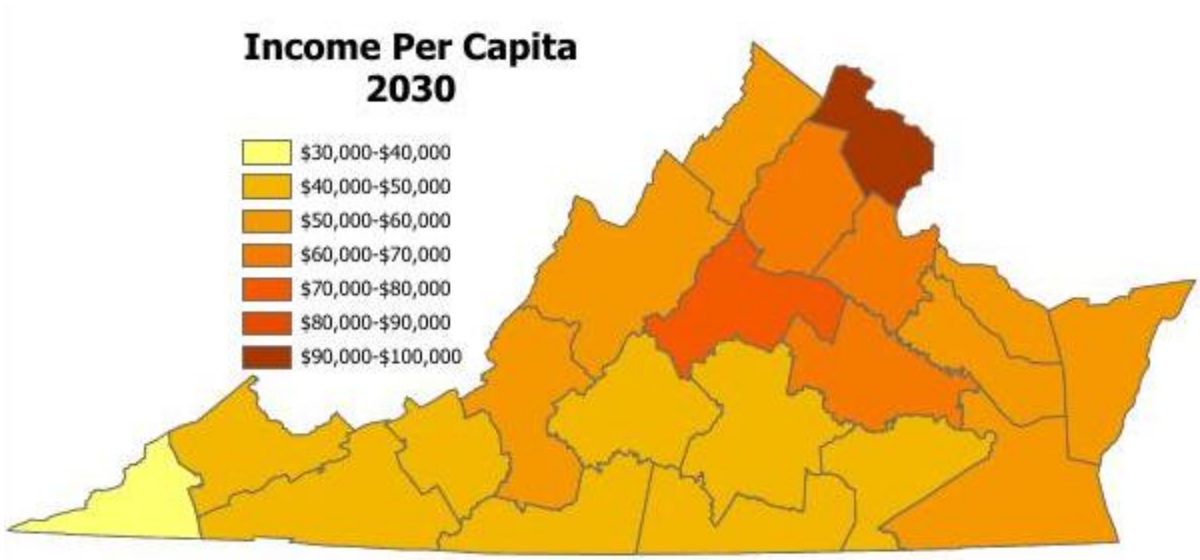

Figure 3. Personal Income per Capita in Each Planning District, 2030. A district whose income per capita equaled *exactly* $40,000 would be assigned to the "$30,000–$40,000" bracket and so on.

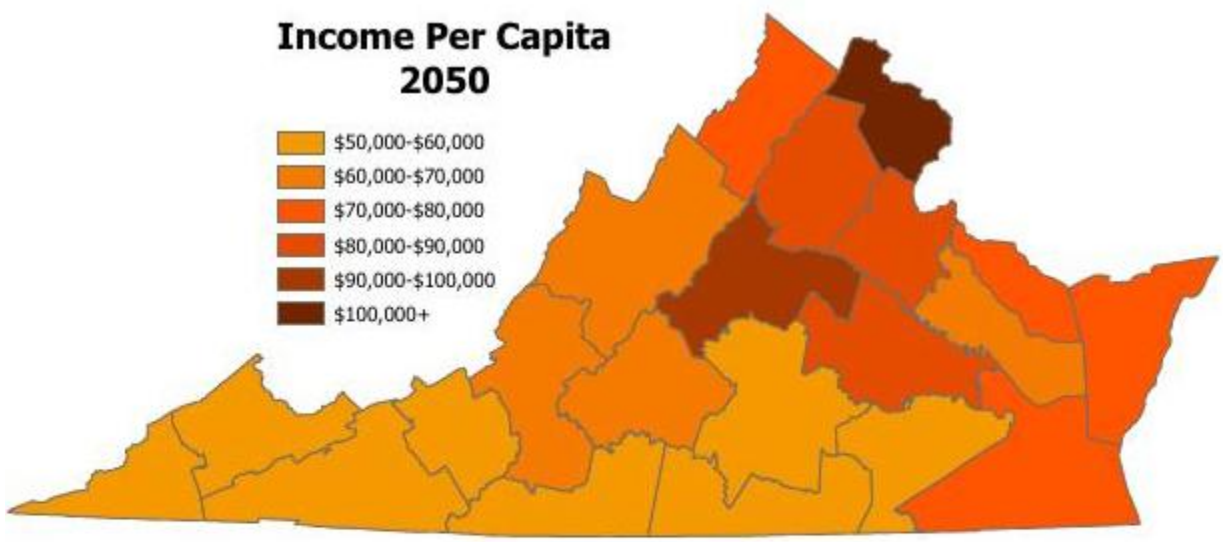

Figure 4. Personal Income per Capita in Each Planning District, 2050. A district whose income per capita equaled *exactly* $30,000 would be assigned to the "$30,000–$40,000" bracket and so on.

The Woods & Poole forecasts of personal income are deflated to a common year's prices, constant 2012 dollars. Therefore, the increasingly dark shades on the maps for succeeding years reflect the forecast that personal income per capita will generally increase over time. The forecasts imply that the Northern Virginia planning district will continue to hold first place. The forecasts appear to imply that the Thomas Jefferson planning district will emerge into second place in the coming decades.

In every year mapped, except 2030, a dozen or more planning districts occupy the two lowest income per capita brackets defined in the map legends. A single planning district, Northern Virginia, consistently occupies the highest bracket in every year mapped, and no more than three districts occupy the two highest brackets. This reflects an unequal geographical distribution of incomes. This finding is consistent with the remark that Bhairavabhatla et al. (2020) made when analyzing the household income data in the 2018 Woods & Poole dataset: "Virginia incomes are not evenly distributed. For year 2017 […] only 3 of the Virginia's 21 PDCs exceed [the state median household income]."

The Rate of Personal Income Change (Maximum and Minimum Rates)

The researchers computed the percentage change in real inflation-adjusted personal income per capita during the preceding 10-year period for every county and city in Virginia, for every year from 1979 to 2024. The highest percentage change in any locality in any 10-year period was 133%. The lowest, or most negative, percentage change was -23.2%. The median percentage change was 21.1%. These statistics correspond to annual growth rates of 8.83%, -2.61%, and 1.93%, respectively.

Residential Turnover and Its Implications for Prioritizing Transport Benefits to Certain Subsets of the Population

Income is one of a number of statistics that planners use to describe the demographic profile of the population in a given jurisdiction.

Several transport planning organizations nationwide employ project prioritization processes that incorporate criteria to target services to disadvantaged individuals or members of groups of special concern. Williams et al. (2019) surveyed 35 metropolitan planning organizations—16 in Florida and 19 in other states—to study systematically the methods they used to incorporate equity into project planning and prioritization. Six of these organizations—five in other states and one in Florida—they subjected to more in-depth examination. Williams et al. (2019) found that minority, low-income, and limited English proficiency populations were the criteria used most pervasively to define a community of concern—that is, a disadvantaged population. They attributed this prevalence to the language in the Code of Federal Regulations Title IV and to the Federal Highway Administration's environmental justice requirements. Other less pervasive criteria included the populations under age 18, aged 65 and older, or with disabilities, as well as the number of households owning no motor vehicle, female-headed households, single-parent families, or renters meeting some definition of cost burdened, such as those spending more than 50% of household income on housing.

Virginia also takes account of disadvantaged populations when ranking potential transport projects (OIPI, 2021). Xu and Dougald (2025) developed an estimation model to provide VDOT and OIPI with cheaper, faster options for estimating the size of the disadvantaged population within a given census tract or census block group. Although the authors identified a general tendency for the disadvantaged population in a given tract to rise over time, variability around this tendency existed, and Xu and Dougald's (2025) sample included some individual census tracts and block groups whose disadvantaged populations fell from one observation to the next (Yiqing Xu, VTRC, "personal communication," October 22, 2025). This variability in the rate and direction of change of the disadvantaged population in a given area invites a question: how stable over time are the demographic features that qualify a neighborhood as disadvantaged?

Task 1 tabulated the population totals in Virginia's cities and counties over time and established the range of values within which the rates of population growth in Virginia's cities and counties have occurred historically during recent decades. That section also tabulated the personal income totals. It established the range of values within which the rates of growth of income per capita—one important demographic feature of the population in a given locality—have occurred historically. This section takes a closer look at the historically observed rates of demographic change on a smaller scale and considers the implications for planners.

The Likelihood of Demographic Change Versus the Speed of Transport Investment

As the construction of a transport facility takes time, the possibility exists that the demographic profile of the community where the effect of the facility will be felt may change between the time the construction is programmed and the time the facility enters service. Gillespie (2021) surveyed literature on (1) the amount of time required to complete certain types of transport investments and (2) the frequency of gentrification and tabulated the amount of time needed to plan and build different types of improvements against the probability that a neighborhood would gentrify (i.e., the probability that its demographic profile would shift) during the construction of the transport improvement.

The Timeline of a Transport Investment

The turnaround time to plan and build a transport improvement depends on the type of improvement. On the lower end of the spectrum, the procurement of new buses for a new school bus route may be completed in 1 year's budget cycle (Idaho Department of Education, 2018). Procurement of new heavy-duty buses for a transit fleet may take 2 years (Federal Transit Administration, 2017; Livermore Amador Valley Transit Authority, 2016). At the upper end of the spectrum, the planning, design, and construction of a light rail transit project may cover one or two decades, depending on its complexity. The Central Corridor Light Rail Transit project in Minneapolis, known as the METRO Green Line, opened for service in 2014, following construction that began in 2010, design that began in 2007, and public involvement that began in 2001 (Metropolitan Council, 2021). Voters approved a planned extension of light rail transit in Seattle in 2016. Construction of the West Seattle portion is projected to be completed in 2031, and construction of the Ballard and downtown Seattle light rail tunnel is projected to be completed in 2036 (SoundTransit, 2021). Highway infrastructure improvements fall in the middle of the spectrum. Inspection of individual Virginia projects via the VDOT interactive Dashboard reveals that once a highway construction project is approved and funded, the planning, design, and construction may take from 2 to 6 years, depending on the project's complexity (VDOT, 2021).

The Likelihood of Gentrification

Hirsch and Schinasi's (2019) and Martin's (2017a, 2017b) findings provide helpful numerical illustrations of the rate of neighborhood change that transport planners can expect to see.

Hirsch and Schinasi (2019) developed a measure of gentrification for use in longitudinal public health studies. They used 1990, 2000, and 2010 census data from Philadelphia to illustrate how their measure works, and they defined each census tract as a neighborhood. Hirsch and Schinasi (2019) defined an “ineligible” tract as any tract whose (1) median household income fell in the uppermost quartile among all census tracts (too affluent to be eligible) or that (2) had a residential population of less than 50 (generally an industrial area). All other tracts were *gentrifiable*, meaning eligible for gentrification. They defined a gentrified tract as one in which the proportion of residents with college degrees increased by more than the median amount for the metropolitan statistical area (MSA) and in which the percentage increase in either gross rent or home value exceeded the median for the MSA. They defined an intensely gentrified tract as one in which the proportion of residents with college degrees increased by more than the median amount for the MSA and in which the percentage increase in either gross rent or home value exceeded the 75th percentile for the MSA. In the 1990–2000 decade, 68 of the roughly 300 census tracts in Philadelphia, or more than 22%, underwent gentrification by Hirsch and Schinasi’s (2019) definition; 36 of these, or 12%, underwent intense gentrification. In the decades from 2000 to 2020, 124 of the census tracts, or more than 41%, underwent gentrification; 78 of these underwent intense gentrification. 35 of the 68 tracts that exhibited gentrification in the first decade exhibited gentrification again in the second decade.

Martin (2017a, 2017b) studied a panel of census returns from the 50 largest cities in the United States as of 1970 through the five censuses from 1970 to 2010. To take advantage of the census data, Martin treated each census tract as a neighborhood. In each census year, Martin defined a gentrifiable tract as a tract that was (1) in the central city and in which (2) the average household income equaled less than 80% of the average household income in the MSA as a whole. Martin tested two alternative definitions of a gentrified tract: (1) a tract in which the change in average household income from one census to the next exceeded the change in average household income in the MSA as a whole by at least 25%—the “weak” definition—and (2) a tract in which the change in average household income exceeded the change in average household income in the MSA as a whole by at least 50%—the “strong” definition. Table 10, computed from tables that Martin (2017a) published, shows the mean, median, minimum, and maximum rates of gentrification among the cities in Martin’s studies in each of the four decades.

Table 10. Annualized Likelihood of Gentrification (derived from Martin 2017a, Tables 1 and 2)

Category	Rate/Year	1970s	1980s	1990s	2000s
Weak gentrification [a]	Mean	1.092%	2.618%	6.567%	4.807%
	Median	0.891%	2.392%	6.366%	4.815%
	Minimum	0.000%	0.000%	2.555%	1.572%
	Maximum	6.098%	7.019%	15.391%	9.343%
Strong gentrification [b]	Mean	0.381%	1.192%	3.671%	3.520%
	Median	0.237%	1.046%	3.421%	3.151%
	Minimum	0.000%	0.000%	1.048%	1.326%
	Maximum	3.058%	5.253%	8.309%	9.343%

[a] 25% more than median income growth rate. [b] 50% more than median income growth rate.

Hirsch and Schinasi (2019) used two definitions of gentrification: a broader definition and a narrower definition of more intense gentrification. Martin (2017a) also used two definitions, employing a set of criteria somewhat different from Hirsch and Schinasi’s (2019) criteria, a broader (weak) definition and a narrower (strong) definition. By any of the four definitions, it was clear that the possibility that an urban neighborhood's demographic character would change in a given period of years was not negligible.

The Timeline of Investment Versus the Likelihood of Gentrification

The previous subsection showed that implementation of service on a new bus route takes perhaps 1 or 2 years, completion of a road project in VDOT's (2021) Six-Year Improvement Program takes up to 6 years, and completion of a light rail line takes 15 to 20 years. If a transport investment project with a time-to-completion of 2, or 6, or 18 years be undertaken to provide accessibility to a disadvantaged population in a gentrifiable neighborhood, what is the likelihood that the disadvantaged population will still be present—that is, that the neighborhood will remain ungentrified—when the transport investment is complete? The estimates of the probability of gentrification per unit time and of the time to complete various types of transport improvements give enough information to compute an answer to this question.

Table 11 starts with the median, mean, minimum, and maximum average annual rates of gentrification for the 2000–2010 decade from Table 10. The 2000–2010 decade exhibited neither the highest nor the lowest rates among those Martin (2017a) documented, and it represents the most recent data Martin studied. Table 11 displays the likelihood that a neighborhood will have gentrified after 2, 6, or 18 years—first under Martin's weak definition of gentrification to exceed by 25% the median income growth rate in the MSA and then under Martin's strong definition of gentrification to exceed by 50%.

Table 11. Probability that a Gentrifiable Tract Will Have Gentrified Within a Certain Period of Time

Category	Weak	Probability	After 2 Years	After 6 Years	After 18 Years
Weak [a]	Mean	4.807%	9.383%	25.591%	58.802%
	Median	4.815%	9.398%	25.628%	58.863%
	Minimum	1.572%	3.119%	9.067%	24.809%
	Maximum	9.343%	17.812%	44.484%	82.890%
Strong [b]	Mean	3.520%	6.917%	19.349%	47.539%
	Median	3.151%	6.203%	17.479%	43.807%
	Minimum	1.326%	2.635%	7.699%	21.365%
	Maximum	9.343%	17.812%	44.484%	82.890%

[a] 25% more than median income growth rate in the 2000–2010 decade. [b] 50% more than median income growth rate in the 2000–2010 decade.

Table 11 indicates that the likelihood that a given disadvantaged neighborhood will gentrify before the completion of a 6-year transport improvement project is not negligible.

The Tendency of Transport Investment to Cause Demographic Change

When a transport planner compares the speed at which neighborhood gentrification can happen with the speed at which a transport system improvement can happen, the planner may well have the sense of aiming at a moving target. Moreover, the previous subsection treated the likelihood of gentrification as a constant parameter, taking no account of the effect that a transport investment itself may have on demographic turnover. Gillespie (2024) consulted literature on (1) the empirical relationship between certain transport investments and residential property values and (2) the empirical relationship between property values and gentrification.

Housing Costs and Gentrification

Many students of gentrification have adopted changes in residential real estate values as one of the criteria by which to define gentrification. Hirsch and Schinasi (2019) defined gentrifiability in terms of median household income and defined gentrification in terms of changes in the proportion of residents with college degrees and changes in gross rent or home value. Martin and Beck (2016) defined gentrifying neighborhoods in terms of average housing prices and the percentage of college-educated adults. All four of the gentrification mapping methods with which Preis et al. (2020) experimented—the methods adopted in Los Angeles, Portland, Seattle, and Philadelphia—included either rental costs, housing prices, or both, among their criteria.

Among the four methods Preis et al. (2020) tested, Philadelphia's housing cost criterion is the most easily adapted to this report's purposes. To identify gentrification, a change in excess of the citywide median of 15.6% in a decade was the critical threshold for gross rent, and a change in excess of the citywide median of 31.7% was the critical threshold for median home value. The higher threshold for homeowners is consistent with the finding that gentrification dislodges renters more readily than homeowners.

It is essential to understand that correlation does not imply causation. That being said, it may be reasonable to suppose that a transport investment that occasioned a local change in gross rents of 15.6% in excess of the citywide median could motivate a current resident to search for cheaper housing and, likewise, a local change in home values 31.7% in excess of the citywide median.

Transport Investment and Residential Property Values

A body of research literature is devoted to the statistical association between the price at which a residential property changes hands, or the rent at which the property is leased, and the property's proximity to certain types of transport facilities. A few ready examples are compiled here regarding rail transit, bus rapid transit, highway noise, and walkability.

Cervero et al. (2004) reviewed the practice of transit-oriented development as of 2002 by surveying and interviewing stakeholders in cities where transit-oriented development was underway and by conducting case studies in 10 U.S. cities. They found that residential properties within walking distance of a rail transit stop generally rented or sold at a premium over the average in the surrounding area. Rents and sale prices sometimes reflected disamenity effects for properties that were very close—for example, within 300 meters—to the transit stop. The rent premia fell in a range from +6.4% in Philadelphia to +more than 45% in Santa Clara County, California. Local economic conditions unrelated to the transit stops significantly influenced the trajectory of rents in a given market.

Acton et al. (2020) conducted a before-and-after study of eleven bus rapid transit developments in 10 U.S. cities. At three of the eleven bus rapid transit systems, residential properties near the bus stops exhibited statistically significant increases in value. at one system, residential properties near the bus stops exhibited statistically significant decreases. The effect on residential property values was statistically insignificant at the other seven systems. When the authors split the sample into single-family properties and multifamily properties, they found that the effect tended to be more positive for multifamily properties.

McElveen et al. (2020) studied 8,100 home sales within a one-mile buffer of Interstate 295 (I-295) in Jacksonville, Florida, during the period from 2012 to 2016. They estimated a hedonic pricing model that included (1) proximity to the centerline of the highway, (2) presence or absence of a sound wall, and (3) the height difference between the centerline and the lot at the point of nearest proximity as explanatory variables. Testing two models with different corrections for spatial autocorrelation, they found that houses standing within 500 feet of I-295 sold at discounts of -3.34% to -4.59% relative to otherwise comparable houses standing more than 1,500 feet from the highway, and houses standing between 500 and 1,500 feet from the highway sold at discounts of -3.15% to -4.02%. They also found that the presence of a sound wall increased house prices by +1.82% to +4.29%. This result meant that the sound wall negated more than one-half of the noise discount in the first model, with coefficient estimates of opposite sign and lesser magnitude, whereas the sound wall would approximately cancel the noise discount in the second model, with coefficient estimates of opposite sign and slightly greater magnitude. However, the elevation of I-295 above the residential lot diminished the benefits of the sound wall.

Literature on walkable neighborhoods suggests that urban changes that bring more consumer destinations within walking distance of a neighborhood may increase property values in that neighborhood. The authors seem to see this finding primarily as a lesson for land use planners, a lesson on the benefits of attracting more amenities into densely settled residential neighborhoods. One can take this literature, nonetheless, as a lesson for transport agencies. Just as one might argue that an investment in reducing travel times across a region could activate agglomeration economies associated with a higher density of employment in a particular industry, one might argue that investments in sidewalks, marked pedestrian crosswalks, and so forth, to the extent that they expand a neighborhood's pedestrian "travelshed," could affect property values associated with walkability.

Cortright (2009) studied a dataset of recent residential property transactions in 15 metropolitan areas. To a list of variables found in other hedonic pricing models of residential real estate, Cortright added a "walk score" based on the walking distance to the nearest destination in each of 13 categories of typical consumer destinations—grocery store, pharmacy, park, and so on—and normalized scoring to a scale of 0 to 100. The report characterized the effect of the walk score by noting the difference in each metropolitan area between a neighborhood with the median walk score for that metropolitan area and a neighborhood with the 75th percentile walk score in the same metropolitan area. The difference ranged from 5 points in the Dallas, Texas, sample to 20 points in the Bakersfield, California, sample. In most cities (10 of 15), the difference fell within the range of 11 to 15 points. In 13 of the 15 metropolitan area regressions, the walk score had a positive and statistically significant coefficient.

The report characterized the meaning of the regression estimates by calculating that for Charlotte, North Carolina, the 17-point difference between the walk score in the median neighborhood and the walk score in the 75th percentile neighborhood would account for roughly a 12.83% premium in property value. Charlotte had the second highest 50%–75% walk score differential and the fourth highest regression coefficient. Had the report taken Phoenix as its example, with the median 50%–75% walk score differential of 12 and a regression coefficient slightly above the median for the group, the differential would account for roughly a 6.18% premium. Had the report taken as its example Bakersfield, whose regression coefficient did not differ significantly from zero, the effect would have been negligible. It must be noted that a transformation in walkability as drastic as the Charlotte example may not be within the scope of a single transport project.

Implications for Planners, Caveats, and Qualifications

Some planning exercises consider the geographic distribution of subsets of special concern within the general population when they prioritize transport projects. The findings noted previously have implications for planning exercises of this sort. Furthermore, the literature on residential turnover and gentrification tends to use models that abstract away from several details that complicate the planner's consideration of the implications of residential turnover and gentrification.

Demographic change can occur under the influence of forces that are largely independent of transport investment. Demographic change can be catalyzed by transport investment. The findings in the previous section suggest two things. First, planning a transport investment whose benefits are expected to accrue to travelers who live in a certain disadvantaged neighborhood is going to be tricky if the project takes a long time to design and build. Second, planning a transport investment whose benefits are expected to accrue to travelers who live in a certain disadvantaged neighborhood is going to be tricky if the project itself is expected to transform the neighborhoods that it serves.

The previous remarks apply, *mutatis mutandis*, to a transport investment that entails disbenefits for local residents. If a new transport facility is expected to entail local disbenefits, such as combustion emissions or noise (Demetillo et al., 2021; Greenberg, 2020; Kerr et al., 2024), the transport agency may wish to study the possibility that the disadvantaged population in the neighborhood of the new facility will exhibit an upward trend. The agency may target a corridor with low assessed property values and low settlement density only to find that low-income residents—possibly relocating from gentrifying neighborhoods elsewhere—are moving into the targeted corridor.

If a transport agency values service to disadvantaged travelers as an explicit criterion in ranking and prioritizing projects, perhaps the office that carries out the ranking ought to consider the risk that disadvantaged travelers will move out of the geographical area that a project is designed to serve. This risk might be represented, for example, by a *discount factor* based on the length of the project timetable and the magnitude of the expected impact.

It is appropriate to acknowledge other details that sometimes mitigate and sometimes complicate the lessons from the previous findings. First, the published studies of gentrification use data at the census block or block group level. If a planner prioritizes projects based on reference to demographic indices aggregated at a larger geographic scale, such as the county and city level or even the census tract level, multiple block groups will be pooled. The risk of demographic change that may be significant at the census block group level will tend to be diluted.

Second, empirical measurement of the likelihood of gentrification depends on the definition of gentrification. The definition of gentrification varies from one published study to another, just as the definition of a disadvantaged population varies from one jurisdiction to another, depending on the local government's equity goals and on the data to which the local planners have access. Preis et al. (2020), as noted previously, examined four definitions adopted in four different U.S. cities and applied each of them in turn to a Boston dataset to see how one's definition would affect one's findings. They applied each of the four methods to the same Boston data and compared the results. They found that the set of census tracts that one identified as gentrifying or at risk of gentrification depended considerably on the definition that one adopted. The total number of "at risk" census tracts varied from as few as 25 by Philadelphia's method to as many as 119 by Seattle's method. In no pairwise comparison, moreover, did the set of "at risk" tracts identified by one method match more than 63% of the "at risk" tracts identified by another method.

Third, neighborhood de-gentrification, or, in some cases, the creation of a low-income neighborhood where no residential neighborhood existed before, is also possible. Cortright (2014) reported that the 2010 census returns showed three times as many urban neighborhoods (census tracts) with poverty rates more than 30% as the number that the 1970 census showed. Part of the increase, no doubt, reflects urbanization and population growth. All the same, the findings indicate that some tracts that were not high-poverty areas in 1970 had become so by 2010.

Fourth, although the published research does show that the probability of demographic change on the timescale of a transport investment (2 to 18 years) appears to be significant when a region's demography is modeled with limited local information, it must be recognized that an observer with boots on the ground, who has a richer set of detailed local information, may perceive gentrification to be neither as unpredictable nor as sudden as the models in the literature are forced to assume. Cortright (2014) found that high-poverty neighborhoods tend to remain so. Of 1,100 urban census tracts with high (≥ 30%) poverty rates in 1970, 750 continued to have poverty rates two or more times the national average in 2010. If gentrification truly resembled a radioactive decay process, such a large fraction would not remain unflipped for 40 years. The researchers whose findings are cited previously to illustrate the probability of gentrification—Hirsch and Schinasi (2019), Martin (2017a), and Preis et al. (2020)—undoubtedly would agree that a knowledgeable observer on the ground in a given neighborhood would be able to recognize the presence or absence of some indicators of incipient gentrification, even if those researchers were unable to include such rich indicators in their models.

Fifth, the previous argument paints real estate appreciation as an unwelcome event that increases involuntary displacement of lower-income residents, denying them the opportunity to capture the benefits of a transport investment. In fact, the correlation between property values and transport investment has multiple causes. Some change in residential property values might be attributed to an influx of wealthier residents bidding up the price of housing. However, some change might be attributed to the fact that residents with better access via public transit or via walking have more income to spend on non-transport goods and services, such as housing upgrades.

Task 2. Confidence Intervals Around Forecasts of Population, Employment, or Income

Bhairavabhatla et al. (2020), compiling trend trackers for a previous VTrans update, studied a selection of forecasts that various local planning agencies made between 1994 and 2013. Bhairavabhatla et al. (2020) compared these forecasts against actual realized values published later.

The researchers had access to Woods & Poole dataset editions published in 2014, 2018, 2021, 2022, 2023, and 2024. VTRC purchased these datasets to compute the six VTrans population and employment trend trackers in past iterations of the VTrans exercise, as described in the Introduction. The most recent year whose values the 2014 edition labeled as historical was 2011, although the values in 2011 and earlier years remained subject to revision in later editions of the dataset.

Woods & Poole do not publish a separate population or employment estimate for every one of Virginia's 95 counties and 38 independent cities. Following BEA's example, Woods & Poole aggregate the numbers for some of the smaller independent cities in Virginia with the county with which they share the longest common border. For example, Woods & Poole do not estimate the population of Rockbridge County, the population of the city of Buena Vista, and the population of the city of Lexington separately for any given year. Instead, they provide one aggregated estimate for the three jurisdictions combined. Because of this method, the number of separate counties, cities, and county-city aggregates in 1 year's estimates amounts to only 105 separate estimates. Confidence intervals may be considered across the following three areas:

- Population.
- Employment.
- Personal income.

Population

Table 12a shows the mean percent error of the 105 population estimates for each lead length of which the available Woods & Poole datasets afford an observation. For example, the value in the top left-hand box indicates that the estimates of population in 2022, which Woods & Poole published in 2014, were 7.72% higher on average than the true (that is, more or less final) 2022 population values recorded as of 2024. The value in the box four spaces further to the right indicates that the estimates of population in 2022, which Woods & Poole published in 2018, were 0.30% lower on average than the true values recorded as of 2024. The boxes in between these two boxes are empty because the researchers did not have access to the Woods & Poole editions published between 2015 and 2017 and, thus, were unable to observe Woods & Poole's estimates of population in 2022 at lead lengths of –7, –6, or –5. The lowest diagonal of filled boxes—the Y–8 forecast of population in 2022, the Y–7 forecast of population in 2021, and so on—represents the set of forecasts Woods & Poole published in 2014. The second lowest diagonal of filled boxes—the Y–4 forecast of population in 2022, the Y–3 forecast of population in 2021, and so on—represents the set of forecasts Woods & Poole published in 2018.

Table 12a. Mean Percent Difference between Forecasts in Years Y-8, Y-7, …, Y+1, and Finalized Population Estimates in Year Y

	Forecast Year										
Year Y	Y-8	Y-7	Y-6	Y-5	Y-4	Y-3	Y-2	Y-1	Y0	Y+1	Y+2
2022 Pop	7.72%				– 0.30%			0.11%	0.00%	0.08%	0
2021 Pop		7.10%				– 0.06%			– 0.06%	– 0.16%	0
2020 Pop			6.70%				2.09%			– 0.02%	0
2019 Pop				6.16%				1.72%			0
2018 Pop					5.37%				1.11%		
2017 Pop						4.68%				0.60%	
2016 Pop							3.82%				
2015 Pop								3.00%			
2014 Pop									2.29%		

Pop = population; Year Y = statistical year for which the forecast was made.

The positive number in the top left cell of the Table 12a means that the 2014 estimate of population in 2022 (the year Y-8 estimate of population in year Y) was a 7.72% overestimate. The zeroes in the right-most column reflect the fact that Woods & Poole deem the population estimates for 2022, which they published in 2024, to be "ground truth" not subject to further revision. In fact, these values were occasionally revised in later editions, but the revisions were quite small.

Table 12b shows the standard deviation of the percent error of the 105 population estimates for each lead length at which the available Woods & Poole datasets afford an observation.

Table 12b. Standard Deviation of Percent Difference between Forecasts in Years Y-8, Y-7, …, Y+1, and Finalized Population Estimates in Year Y

	Forecast Year										
Year Y	Y-8	Y-7	Y-6	Y-5	Y-4	Y-3	Y-2	Y-1	Y0	Y+1	Y+2
2022 Pop	6.67%				3.17%			3.04%	0.90%	0.27%	0
2021 Pop		6.12%				2.66%			2.66%	0.22%	0
2020 Pop			5.77%				3.39%			2.46%	0
2019 Pop				4.46%				1.94%			0
2018 Pop					3.97%				1.44%		
2017 Pop						3.54%				1.14%	
2016 Pop							2.99%				
2015 Pop								2.42%			
2014 Pop									2.04%		

Pop = population; Year Y = statistical year for which the forecast was made.

In general, the mean error and the standard deviation of the errors tend to become smaller as the lead length becomes shorter.

The mean error of a set of 105 estimates made 4 years in advance was not the same in both sets of estimates for which the computation could be made. That is, the Y-4 population forecasts for 2018, published in 2014, show a mean error of 5.37%, a substantial overestimate, whereas the Y-4 population forecasts for 2022, published in 2018, show a mean error of -0.30%, a slight underestimate. The researchers carried out a t-test of equality of means between two groups of observations to test the null hypothesis that the mean errors in the two groups of Y–4 forecasts were equal. Given that the number of groups is k and the number of forecasts in each group is N, the distribution of the test statistic is a t-distribution with k·N-k degrees of freedom, 208 degrees of freedom in this case. Under the null hypothesis that the means are equal, a test statistic value greater than or equal to 11.42, which the researchers obtained, would be less than 0.001, and the probability of a value less than or equal to –11.42 would be likewise. Therefore, the null hypothesis was rejected. Tests of equality among the mean errors in the groups of forecasts at Y-3, Y-2, and Y-1 were likewise rejected with high confidence. This finding implies that 1 year can contain a systematic positive or negative shock to population change in all or most counties and cities, whereas another year can include a negligible shock in all or most counties and cities.

The standard deviation of the errors in a set of 105 estimates made 4 years in advance was not the same in both sets of estimates for which the computation could be made. The Y-4 population forecasts for 2018, published in 2014, show errors with a standard deviation of 3.97 percentage points, while the Y-4 population forecasts for 2022, published in 2018, show errors with a standard deviation of 3.17 percentage points. The researchers conducted Welch's test of equality of variances between two groups of observations to test the null hypothesis that the variances of the errors in the two groups of Y-4 forecasts were equal. Note that the test hypothesis is stated in terms of the variance, which equals the square of the standard deviation. The number of groups being k and the number of forecasts in each group being N, the distribution of the test statistic W is approximately an F distribution with k-1 and k·N-k degrees of freedom, 1 degree of freedom and 208 degrees of freedom in this case. Under the null hypothesis that the variances are equal, the likelihood of obtaining a value of the test statistic greater than or equal to the value of 29,869, which the researchers obtained, would be infinitesimal (p-value = 3.40×10^{-220}). Therefore, the null hypothesis was rejected. Tests of equality among the variances of the errors in the groups of forecasts at Y-3, Y-2, Y-1, Y0, and Y+1 were likewise rejected overwhelmingly.

These findings imply that 1 year can contain a sizable shock to population change, or a bigger "surprise," positive in some counties and cities and negative in others, whereas another year can contain a negligible shock, or almost no "surprise," in most counties and cities. In general, the accumulation of surprises during an interval of 4 years will amount to more forecast error than the accumulation of surprises during a shorter period—that is, more forecast error 4 years in advance and less forecast error 2 years in advance—but these surprises are inherently unpredictable. One 4-year interval can be "noisier" than another.

The accuracy of the forecast must be judged *with respect* to the final true value, which becomes a matter of historical record 2 years after the year to which the statistic applies. The means in Table 12a measure the average error of the 105 local forecasts with respect to the true final values. The standard deviations in Table 12b measure the variability of the errors in the 105 local forecasts *around the average error* of the forecasts. Table 12c shows the root mean squared differences between the population forecasts and the final population estimates. Table 12c provides a practical confidence interval. If we assume that the uncertainty in the forecast can be represented approximately by a random normal variable, then we can expect that most (two-thirds) of the time, the difference between the forecast and the final value will be less than the amount shown in Table 12c. For example, consider the 10.20% in the upper left cell of Table 12c. When making population forecasts 8 years ahead, one would expect that for most (two-thirds) of localities, the difference between forecast and observed population will differ by less than 10.20%.

Table 12c. Root Mean Squared Percent Difference between Forecasts in Years Y-8, Y-7, …, Y+1, and Finalized Population Estimates in Year Y

	Forecast Year										
Year Y	Y-8	Y-7	Y-6	Y-5	Y-4	Y-3	Y-2	Y-1	Y0	Y+1	Y+2
2022 Pop	10.20%				3.19%			3.04%	0.90%	0.28%	0
2021 Pop		9.37%				2.67%			2.67%	0.27%	0
2020 Pop			8.84%				3.98%			2.46%	0
2019 Pop				7.60%				2.59%			0
2018 Pop					6.68%				1.82%		
2017 Pop						5.87%				1.29%	
2016 Pop							4.85%				
2015 Pop								3.85%			
2014 Pop									3.07%		

Pop = population; Year Y = statistical year for which the forecast was made.

Table 12c accounts for both the systematic statewide average errors of Table 12a and the error variability from one county to the next of Table 12b. The variance of the forecast errors, measured around the average error, is $E[(X - X_{avg})^2] = E[X^2] - X_{avg}^2$. The mean squared error of the forecasts is the larger quantity $E[X^2] = E[(X - X_{avg})^2] + X_{avg}^2$. The mean squared error of the forecasts is the quantity $[(\text{standard deviation})^2 + (\text{mean})^2]$ and the root mean squared error is $[(\text{standard deviation})^2 + (\text{mean})^2]^{½}$. For example, Table 12a shows that the population forecasts for 2022 made 8 years in advance, in 2014, were off by an average of +7.72%. On average, Woods & Poole overestimated what each locality's population would be in 2022. Table 12b shows that the standard deviation of the forecasts, around this average, was +6.67%. Woods & Poole's estimates were further on the low side for some localities and further to the high side for others. The mean squared error of the forecasts, *around the true final values*, was $(0.0667)^2 + (0.0772)^2 = 0.01040873$. The root mean squared error was $(0.01040873)^{½} = 0.1020$, or 10.20% in Table 12c.

These root mean squared differences are larger than the standard deviations in Table 12b because they measure the scatter of the forecasts around the finalized year Y+2 estimates, rather than the scatter of the forecast errors around their own mean. In some of the numbers, the greater magnitude becomes undetectable when rounded to two decimal places.

Employment

Table 13a shows the mean percent error of the 105 employment estimates for each lead length of which the available Woods & Poole datasets afford an observation.

Table 13a. Mean Percent Difference between Forecasts in Years Y-8, Y-7, …, Y+1, and Finalized Employment Estimates in Year Y

	Forecast Year										
Year Y	Y-8	Y-7	Y-6	Y-5	Y-4	Y-3	Y-2	Y-1	Y0	Y+1	Y+2
2022 Emp	7.78%				4.57%			0.79%	– 1.88%	– 1.38%	0
2021 Emp		10.82%				7.44%			3.87%	0.06%	0
2020 Emp			14.08%				10.53%			0.97%	0
2019 Emp				6.28%				2.89%			0
2018 Emp					6.51%				2.89%		
2017 Emp						6.27%				2.11%	
2016 Emp							5.68%				
2015 Emp								5.24%			
2014 Emp									5.19%		

Emp = employment; Year Y = statistical year for which the forecast was made.

Table 13b shows the standard deviation of the percent error of the 105 employment estimates for each lead length of which the available Woods & Poole datasets afford an observation.

Table 13b. Standard Deviation of Percent Difference between Forecasts in Years Y-8, Y-7, …, Y+1, and Finalized Employment Estimates in Year Y

	Forecast Year										
Year Y	Y-8	Y-7	Y-6	Y-5	Y-4	Y-3	Y-2	Y-1	Y0	Y+1	Y +2
2022 Emp	16.52%				7.42%			3.98%	3.76%	2.77%	0
2021 Emp		16.32%				7.10%			3.70%	2.63%	0
2020 Emp			15.83%				6.58%			2.59%	0
2019 Emp				14.26%				4.81%			0
2018 Emp					13.93%				4.16%		
2017 Emp						13.44%				3.49%	
2016 Emp							13.76%				
2015 Emp								13.15%			
2014 Emp									12.42%		

Emp = employment; Year Y = statistical year for which the forecast was made.

In general, the mean error and the standard deviation of the errors tend to become smaller as the lead length becomes shorter. This pattern is somewhat less stable than the pattern in the population forecasts, however, as the computation of root mean squared differences will show in the following sections.

Comparing the standard deviations in Table 13b, variability of errors in the employment estimates, with those in Table 12b, variability of errors in the population estimates, shows that

Woods & Poole's forecasts of employment at the county and city levels tend to be somewhat more widely scattered than their forecasts of population at the county and city levels. In Table 13a, the forecasts published in 2014 and 2018 overestimated employment in 2020 and 2021 especially badly. That is, the Y-6 and Y-2 forecasts of employment in 2020 tended to overestimate the true 2020 county and city employment levels by rather a lot and, likewise, the Y-7 and Y-3 forecasts of employment in 2021. These overestimates presumably can be attributed to the large, unexpected negative shocks to employment that resulted from the COVID-19 pandemic lockdown.

The standard deviation of the errors in a set of 105 estimates made 4 years in advance was not the same in both sets of estimates for which the computation could be made. The Y-4 employment forecasts for 2018, published in 2014, show errors with a standard deviation of 13.93 percentage points, while the Y-4 employment forecasts for 2022, published in 2018, show errors with a standard deviation of 7.42 percentage points. The researchers conducted Welch's test of equality of variances between two groups of observations to test the null hypothesis that the variances of the errors in the two groups of Y-4 forecasts were equal. Note that the test hypothesis is stated in terms of the variance, which equals the square of the standard deviation. The distribution of the test statistic W again is approximately an F distribution with 1 degree of freedom and 208 degrees of freedom. Under the null hypothesis that the variances are equal, the likelihood of obtaining a value of the test statistic greater than or equal to the value of 251, which the researchers obtained, would be infinitesimal (p-value = 1.27×10^{-37}). Therefore, the null hypothesis was rejected. This result is many orders of magnitude larger than the likelihood of the F statistic computed previously for the same test regarding the population estimates, but it is infinitesimal nonetheless. Tests of equality among the variances of the errors in the groups of forecasts at Y-3, Y-2, Y-1, Y0, and Y+1 were likewise rejected overwhelmingly. As the tests on the population forecasts in the previous section did, these findings similarly imply that 1 year can contain unexpected shocks to employment that are greater in number or magnitude than the shocks that another year will contain.

The previous remarks about the mean squared error of the population forecasts also apply here. For example, given that the errors of the 105 local employment forecasts for 2022 made 8 years in advance, in 2014, had a mean value of 7.78% and a standard deviation of 16.52%, the mean squared error of the forecasts with respect to the true final employment numbers for 2022 was $[(0.0778)^2 + (0.1652)^2] = 0.03334388$, and the root mean squared error was $(0.03334388)^{½} = 0.1826$, or 18.26%.

Table 13c shows the root mean squared differences between the employment forecasts analyzed previously and the finalized employment estimates.

Table 13c. Root Mean Squared Percent Difference between Forecasts in Years Y-8, Y-7, …, Y+1, and Finalized Employment Estimates in Year Y

	Forecast	**Year**									
Year Y	Y-8	Y-7	Y-6	Y-5	Y-4	Y-3	Y-2	Y-1	Y0	Y+1	Y +2
2022 Emp	18.26%				8.72%			4.06%	4.20%	3.09%	0
2021 Emp		19.58%				10.28%			5.36%	2.63%	0
2020 Emp			21.18%				12.42%			2.77%	0

	Forecast	Year									
Year Y	Y-8	Y-7	Y-6	Y-5	Y-4	Y-3	Y-2	Y-1	Y0	Y+1	Y +2
2019 Emp				15.58%				5.61%			0
2018 Emp					15.38%				5.06%		
2017 Emp						14.83%				4.08%	
2016 Emp							14.88%				
2015 Emp								14.16%			
2014 Emp									13.46%		

Emp = employment; Year Y = statistical year for which the forecast was made.

The tendency for forecasts of more remote future years to show larger discrepancies from the eventual, finalized estimates becomes less pronounced when the root mean squared differences are used as the measure of the discrepancies. The set of Y-6 forecasts shows the largest root mean squared differences, for example. It appears that *ex ante* forecasts of employment in the years affected by the COVID-19 lockdown were least accurate. This observation is reflected in the mean percent differences and in the root mean squared differences but not in the standard deviations of the percent differences.

Personal Income

Table 14a shows the mean percent error of the 105 personal income estimates for each lead length of which the available Woods & Poole datasets afford an observation.

Table 14a. Mean Percent Difference between Forecasts in Years Y-8, Y-7, …, Y+1, and Finalized Personal Income Estimates in Year Y

	Forecast	Year									
Year Y	Y-8	Y-7	Y-6	Y-5	Y-4	Y-3	Y-2	Y-1	Y0	Y+1	Y+2
2022 PerInc	3.75%				1.32%			0.79%	– 0.98%	0.54%	0
2021 PerInc		– 2.39%				– 4.28%			– 4.85%	– 6.43%	0
2020 PerInc			0.21%				– 1.44%			0.31%	0
2019 PerInc				2.25%				0.75%			0
2018 PerInc					6.50%				2.89%		
2017 PerInc						0.90%				– 0.82%	
2016 PerInc							1.85%				
2015 PerInc								0.08%			
2014 PerInc									2.08%		

PerInc = personal income; Year Y = statistical year for which the forecast was made.

Table 14b shows the standard deviation of the percent error of the 105 personal income estimates for each lead length of which the available Woods & Poole datasets afford an observation.

Table 14b. Standard Deviation of Percent Difference between Forecasts in Years Y-8, Y-7, …, Y+1, and Finalized Personal Income Estimates in Year Y

	Forecast	Year									
Year Y	Y-8	Y-7	Y-6	Y-5	Y-4	Y-3	Y-2	Y-1	Y0	Y+1	Y+2
2022 PerInc	14.29%				7.25%			4.79%	4.14%	4.18%	0
2021 PerInc		12.20%				5.97%			4.14%	3.50%	0
2020 PerInc			12.21%				5.63%			3.83%	0
2019 PerInc				11.97%				5.24%			0
2018 PerInc					13.93%				4.16%		
2017 PerInc						11.19%				4.53%	
2016 PerInc							10.02%				
2015 PerInc								9.08%			
2014 PerInc									8.60%		

PerInc = personal income; Year Y = statistical year for which the forecast was made.

In general, the mean error and the standard deviation of the errors tend to become smaller as the lead length becomes shorter. Comparing the standard deviations in Table 13b, variability of errors in the employment estimates, with those in Table 14b, variability of errors in the personal income estimates, shows that Woods & Poole's forecasts of personal income at the county and city levels and their forecasts of employment at the county and city levels tend to have about an equally wide scatter, both being somewhat more widely scattered than their population forecasts.

The standard deviation of the errors in a set of 105 estimates made 4 years in advance was not the same in both sets of estimates for which the computation could be made. The Y-4 personal income forecasts for 2018, published in 2014, show errors with a standard deviation of 13.93 percentage points, while the Y-4 personal income forecasts for 2022, published in 2018, show errors with a standard deviation of 7.25 percentage points. The researchers conducted Welch's test of equality of variances between two groups of observations to test the null hypothesis that the variances of the errors in the two groups of Y–4 forecasts were equal. The distribution of the test statistic W again is approximately an F distribution with 1 degree of freedom and 208 degrees of freedom. Under the null hypothesis that the variances are equal, the likelihood of obtaining a value of the test statistic greater than or equal to the value of 1,785, which the researchers obtained, would be infinitesimal (p-value $\ll 0.01$). Therefore, the null hypothesis was rejected. Tests of equality among the variances of the errors in the groups of forecasts at Y-3, Y-2, Y-1, Y0, and Y+1 were likewise rejected. The null hypothesis concerning the three sets of Y-1 forecasts—income forecasts made in 2014, 2018, and 2021 for the years 2015, 2019, and 2022, respectively—came closer to passing than any other test hypothesis. This F statistic, with a value of 11.6, would happen with likelihood 1.35×10^{-5} if the variances were equal (p-value = 1.35×10^{-5}). As the tests on the population and the employment forecasts implied, these findings similarly imply that one year may happen to contain unexpected shocks to personal income that are greater in number or magnitude than the shocks that another year will contain.

The previous remarks about the mean squared error of the population forecasts also apply here. For example, given that the errors of the 105 local personal income forecasts for 2022 made

8 years in advance, in 2014, had a mean value of 3.75% and a standard deviation of 14.29%, the mean squared error of the forecasts with respect to the true final employment numbers for 2022 was $[(0.0375)^2 + (0.1429)^2] = 0.02182666$. The root mean squared error was $(0.02182666)^{½} = 0.1477$, or 14.77%.

Table 14c shows the root mean squared differences between the personal income forecasts analyzed previously and the finalized personal income estimates.

Table 14c. Root Mean Squared Percent Difference between Forecasts in Years Y-8, Y-7, …, Y+1, and Finalized Personal Income Estimates in Year Y

	Forecast Year										
Year Y	Y-8	Y-7	Y-6	Y-5	Y-4	Y-3	Y-2	Y-1	Y0	Y+1	Y+2
2022 PerInc	14.77%				7.37%			4.85%	4.26%	4.21%	0
2021 PerInc		12.43%				7.34%			6.38%	7.32%	0
2020 PerInc			12.21%				5.81%			3.84%	0
2019 PerInc				12.18%				5.29%			0
2018 PerInc					15.38%				5.07%		
2017 PerInc						11.23%				4.61%	
2016 PerInc							10.19%				
2015 PerInc								9.08%			
2014 PerInc									8.85%		

PerInc = personal income; Year Y = statistical year for which the forecast was made.

Summary of Confidence Interval Analysis

In the forecasts of each of the three statistics—total population, total employment, and total personal income—the mean error and the standard deviation of the errors generally tend to become smaller as the lead length becomes shorter. This finding is expected. The number of remaining future surprises decreases as the date to which the forecast applies draws closer.

The fact that the number of surprises in a given year could differ so much, from one year to another, that the accuracy of a Y-4 forecast in one year would differ with statistical significance from the accuracy of a Y-4 forecast in another year, may not have been expected. It is notable and, at the same time, quite plausible.

The population forecasts tend to be less scattered than the employment and personal income forecasts at any given lead length. This finding presumably reflects the fact that birth and death rates and the cost of migration constrain 1 year's population to be strongly correlated with the previous year's population. This being the case, population changes will tend to be less volatile than employment or income changes, and population will be easier to forecast.

In the available editions of the Woods & Poole package, positive mean errors—that is, mean errors greater than zero—preponderate in the total population and total employment forecasts. The researchers *do not* conclude that Woods & Poole's model systematically overestimates future population and employment. They suppose that the observed pattern is a peculiarity of the 2014–2024 decade which the available editions happen to cover, and that if a longer sample of Woods & Poole estimates were available, the overestimates and underestimates would show a more even balance.

Three qualifying remarks are in order. First, the fact that planners customarily forecast travel demand 20 to 40 years into the future means that a measurement of the degree of reliability in forecasts up to *8* years in advance falls well short of what planners would like to have. Measurement of the accuracy of longer range forecasts, if feasible, would add to the usefulness of the above findings.

Some sense of the degree of uncertainty in in longer range forecasts may be inferred from the comparison in Bhairavabhatla et al. (2020) between the population projections for 2045 in various jurisdictions in northern Virginia that the Cooper Center published in 2017 and the population projections for the same year in the same jurisdictions that the Metropolitan Washington Council of Governments published in 2018. For some individual jurisdictions, these two independent population forecasts 27 or 28 years in the future differed from one another by as much as 37%. Sometimes the Cooper Center projection was higher, and sometimes the Metropolitan Washington Council of Governments projection was higher. Among the 14 jurisdictions whose population forecasts were compared, the mean squared difference amounted to 0.05015972—that is, the root mean squared difference was 22.396%.

Second, the previous analysis ignored the possibility that the residual discrepancies between the forecast values and the true final values, modeled as stochastic errors, are heteroscedastic. In fact, it is likely that the forecast discrepancies in the jurisdictions that have more total population, more total employment, and more total personal income tend to be larger in absolute terms and smaller in percentage terms than the forecast discrepancies in the jurisdictions with smaller totals. Bhairavabhatla et al. (2020) observed, "Generally speaking, forecasts for smaller entities tend to have a larger percent error than those of larger entities."

Third, although more information may always be better for forecasters than less information, any 1 year's contribution to the pool of information can be *un*representative of the full picture. A sense of the extent to which a few years' worth of additional news can transform expectations about the value of a statistic in a future year is evident in forecasts from the city of Williamsburg, Virginia, which Bhairavabhatla et al. (2020) consulted. The city published in 1981 a forecast of its year 2000 population and published in 1989 another forecast of its year 2000 population. The forecast 19 years in advance underestimated the 2000 census count by 7%. The forecast 8 years later overestimated the census count by 13%. The city published in 1998 a forecast of its year 2010 population and published in 2006 another forecast of its year 2010 population. The forecast 12 years in advance underestimated the 2010 census count by 2%. The forecast 8 years later overestimated the 2010 census count by 18%.

Task 3. Exploratory Planning Applications of VTrans Statistics

The VTrans framework, including the trend trackers, exists first and foremost as a source of information for the CTB in setting goals and prioritizing investment. The researchers conjectured that if the trend trackers are meaningful guides for setting high-level investment policy then they may also have applications to planning at a smaller scale. The researchers made several sample computations using the population, employment, and income estimates, sometimes in combination with other publicly available data series. Each of these sample computations explored a method for applying the VTrans trend trackers to planning at the regional or local level. Four applications were developed:

- Population density as a factor in the viability of fixed-route bus service.
- Household income as a factor in automobile ownership and dependence on transit.
- Population and income as correlates of real estate market values.
- Population and employment forecasts as proxies for jobs-housing ratio forecasts.

Population Density as a Factor in the Viability of Fixed-Route Bus Service

The *Transit Capacity and Quality of Service Manual* (TCQSM) cites among its references a publication that suggests that one of the criteria for the viability of a fixed-route bus service is the population density in the service area. The citation identifies a density of about 5,000 persons per square mile as the threshold at which fixed-route service becomes cost effective. It identifies a density of about 16,000 persons per square mile as the threshold that is truly favorable for fixed-route transit (National Academies of Sciences, Engineering, and Medicine [NASEM], 2013). The original article provides density estimates in households per hectare; the TCQSM provides ratios to make unit conversions to persons per square mile.

Historical and Future Estimates Using Woods & Poole Population Estimates

The researchers' 2023 memorandum in support of the VTrans exercise included an estimate of what the Woods & Poole population estimates implied about the largest contiguous area in each planning district that would possess a population density greater than or equal to 5,000 people per square mile, as well as the largest contiguous area that would have a population density greater than or equal to 16,000 people per square mile.

Tables 15a and 15b reproduce the estimates for 2020, 2040, and 2060 from the 2023 technical memorandum. The estimates for 2020 are based on historical population statistics in the Woods & Poole dataset and the estimates for 2040 and 2060 are based on forecasts.

Considerations other than population density contribute to the decision to establish a fixed-route bus service. At present, approximately 35 entities operate fixed-route services in Virginia's counties and cities (Grace Stankus, Virginia Department of Rail and Public Transit, "personal communication," February 7, 2025). These entities operate routes in parts of every planning district except districts 1 (Lenowisco), 17 (Northern Neck), and 18 (Middle Peninsula). To make an exact count of them is no trivial exercise. For example, some of the services that belong to the Virginia Regional Transit group have an independent identity, both online and in the Virginia Department of Rail and Public Transportation database, whereas others do not.

Table 15a. Estimated Largest Contiguous Area with More Than 5,000 Persons per Square Mile

	2020		2040		2060	
Planning District	**Est. Area**	**Est. Pop.**	**Est. Area**	**Est. Pop.**	**Est. Area**	**Est. Pop.**
Lenowisco	0.02	73	0.02	56	0.01	40
Cumberland Plateau	0.00	0	0.00	1	0.00	0
Mount Rogers	1.18	3,533	1.23	3,704	1.26	3,780
New River Valley	1.22	3,647	1.51	4,525	1.84	5,509
Roanoke Valley-Alleghany	14.37	43,106	14.55	43,635	14.62	43,851
Central Shenandoah	7.83	23,504	9.90	29,690	12.22	36,675
Northern Shenandoah	3.82	11,450	5.64	16,932	8.15	24,460
Northern Virginia	109.07	327,222	170.71	512,133	306.08	918,247
Rappahannock-Rapidan	0.00	0	0.00	3	0.01	20
Thomas Jefferson	8.62	25,865	10.90	32,706	13.51	40,515
Central Virginia	9.32	27,949	10.73	32,190	12.13	36,400
West Piedmont	0.65	1,957	0.56	1,686	0.49	1,480
Southside	0.00	0	0.00	0	0.00	0
Commonwealth Regional	0.00	0	0.00	0	0.00	2
Richmond Regional (PlanRVA)	36.20	108,589	40.45	121,337	44.13	132,388
George Washington	2.67	8,019	4.76	14,283	7.85	23,549
Northern Neck	0.00	0	0.00	0	0.00	0
Middle Peninsula	0.29	884	0.36	1,084	0.43	1,292
Crater	2.19	6,566	2.23	6,693	2.19	6,557
Accomack-Northampton	0.00	0	0.00	0	0.00	0
Hampton Roads	41.27	123,820	40.54	121,625	38.73	116,197

Est. = estimated; Pop. = population.

Table 15b. Estimated Largest Contiguous Area with More Than 16,000 Persons per Square Mile

	2020		2040		2060	
Planning District	**Est. Area**	**Est. Pop.**	**Est. Area**	**Est. Pop.**	**Est. Area**	**Est. Pop.**
Lenowisco	0.00	14	0.00	10	0.00	7
Cumberland Plateau	0.00	0	0.00	0	0.00	0
Mount Rogers	0.14	1,447	0.15	1,533	0.16	1,573
New River Valley	0.13	1,302	0.17	1,656	0.21	2,062
Roanoke Valley-Alleghany	2.71	27,056	2.68	26,820	2.64	26,435
Central Shenandoah	1.69	16,935	1.94	19,435	2.19	21,881
Northern Shenandoah	0.51	5,134	0.78	7,842	1.16	11,646
Northern Virginia	5.04	50,448	6.05	60,524	8.47	84,696
Rappahannock-Rapidan	0.00	0	0.00	0	0.00	1
Thomas Jefferson	1.54	15,375	1.93	19,333	2.38	23,816
Central Virginia	1.69	16,935	1.94	19,435	2.19	21,881
West Piedmont	0.06	618	0.05	521	0.05	451
Southside	0.00	0	0.00	0	0.00	0
Commonwealth Regional	0.00	0	0.00	0	0.00	0
Richmond Regional (PlanRVA)	4.40	43,973	4.47	44,691	4.39	43,905
George Washington	0.22	2,168	0.37	3,717	0.57	5,732
Northern Neck	0.00	0	0.00	0	0.00	0
Middle Peninsula	0.03	295	0.04	365	0.04	436
Crater	0.30	3,003	0.30	3,044	0.30	2,955
Accomack-Northampton	0.00	0	0.00	0	0.00	0
Hampton Roads	3.66	36,594	3.22	32,225	2.74	27,353

Est. = estimated; Pop. = population.

The factors favorable for a demand-responsive service have been less intensively studied. Furthermore, the population density may be less important for a demand-responsive service. Twenty-three entities operate Americans with Disabilities Act-compliant paratransit services, most of which are offered in tandem with a fixed-route service. Ten entities operate demand-responsive transit available to the broader public. One of these services, Mountain Empire Transit, operates in the Lenowisco planning district, where no fixed-route transit runs.

These estimates were a relatively simple computation that a district-level planner might make to foresee the viability of fixed-route bus service in his/her district. The reader will note that one could, in fact, make a precise historical tally of the largest contiguous area that meets each of these population density criteria using block- or tract-level census data. Such a precise tally would serve as a means of validating—or of invalidating—the simple estimation method described in this first section.

Historical Tallies Using Block Group Data from the 2020 Census

The researchers prepared historical tallies and maps of the largest contiguous area in each planning district, using block group-level data from the 2020 census. Comparison of these computations with the 2020 area and population estimates in Tables 15a and 15b affords an assessment of the accuracy of the estimation method.

Table 16 juxtaposes the estimates for 2020 and the exact tallies for the same year, for all planning districts.

Table 16. Largest Contiguous Area with More Than 5,000 Persons per Square Mile: Estimates with County and City Data versus Exact Tallies with Census Block Group Data

Planning District	2020 Est. Area	(Est.) Est. Pop.	2020 Area	(Exact) Pop.
Lenowisco	0.02	73	0.08	826
Cumberland Plateau	0.00	0	0.00	0
Mount Rogers	1.18	3,533	0.00	0
New River Valley	1.22	3,647	4.30	23,685
Roanoke Valley-Alleghany	14.37	43,106	0.00	2,418
Central Shenandoah	7.83	23,504	1.86	9,937
Northern Shenandoah Valley	3.82	11,450	0.00	0
Northern Virginia	109.07	327,222	161.62	836,486
Rappahannock-Rapidan	0.00	0	0.00	0
Thomas Jefferson	8.62	25,865	2.68	14,289
Central Virginia	9.32	27,949	0.28	2,151
West Piedmont	0.65	1,957	0.00	0
Southside	0.00	0	0.00	0
Commonwealth Regional	0.00	0	0.00	0
Richmond Regional (PlanRVA)	36.20	108,589	17.68	93,399
George Washington	2.67	8,019	1.04	5,792
Northern Neck	0.00	0	0.00	0
Middle Peninsula	0.29	884	0.00	0
Crater	2.19	6,566	0.34	3,166
Accomack-Northampton	0.00	0	0.00	0
Hampton Roads	41.27	123,820	27.76	149,746

Est. = estimated; Pop. = population.

In the 10 planning districts for which the exact calculation returned populations and areas of zero—namely Cumberland Plateau, Mount Rogers, Northern Shenandoah, Rappahannock-Rapidan, West Piedmont, Southside, Commonwealth, Northern Neck, Middle Peninsula, and Accomack-Northampton—the estimation method also returned very small populations and very small areas, often zero even out to two decimal places. In the three planning districts for which the exact calculation returned large areas and large populations (more than 17 square miles and more than 90,000 people)—namely Northern Virginia, Richmond, and Hampton Roads—the estimation method also returned large areas and populations area estimate in Richmond and the population estimate in Northern Virginia off by more than a factor of two.

In the four planning districts for which the exact calculation returned a non-zero area of less than 1 square mile and a population of less than 5,000—namely, Lenowisco, Crater, Roanoke Valley-Alleghany, and Central Virginia—the estimation method returned mixed results. It estimated a comparably small area and population in the Lenowisco and Crater Districts. However, it considerably overestimated the area and population in the Roanoke Valley-Alleghany and Central Virginia Districts. In the four planning districts for which the exact calculation returned an intermediate area and population (one-to-five square miles and 5,000 to 90,000 people)—namely New River Valley, Central Shenandoah, Thomas Jefferson, and George Washington—the estimation method returned mixed results. It markedly underestimated the area and population in the New River Valley District, it markedly overestimated the area and population in the Central Shenandoah District, and it somewhat overestimated the area and population in the Thomas Jefferson and George Washington Districts.

Figures 5 and 6 show the maps of high-density areas in two representative planning districts: the heavily urbanized Richmond Regional District and the moderately urbanized Thomas Jefferson District.

Figure 5 shows that the Richmond Regional Planning District features two sizeable clusters within the city limits of Richmond. The search algorithm that the researchers employed to build clusters in which the average population density remained over 5,000 people per square mile forbade, at any step of the search, the addition of a census block group that brought the average below 5,000. The two clusters within Richmond lie only one census block group apart. It is quite possible that a slightly more sophisticated or more permissive algorithm would have combined them into a single cluster.

Figure 6 shows that the Thomas Jefferson district's largest cluster lies mainly within the city limits of Charlottesville.

The estimation method produced a pattern of larger high-density areas and smaller high-density areas in 2020 that matched, grossly, the pattern that the exact calculation revealed. A further step, possibly of interest, would be to reproduce the exact calculation using data from the 2000 census or, when they become available, data from the 2030 census, to see whether the exact calculation confirms the trends that the estimation method appears to show.

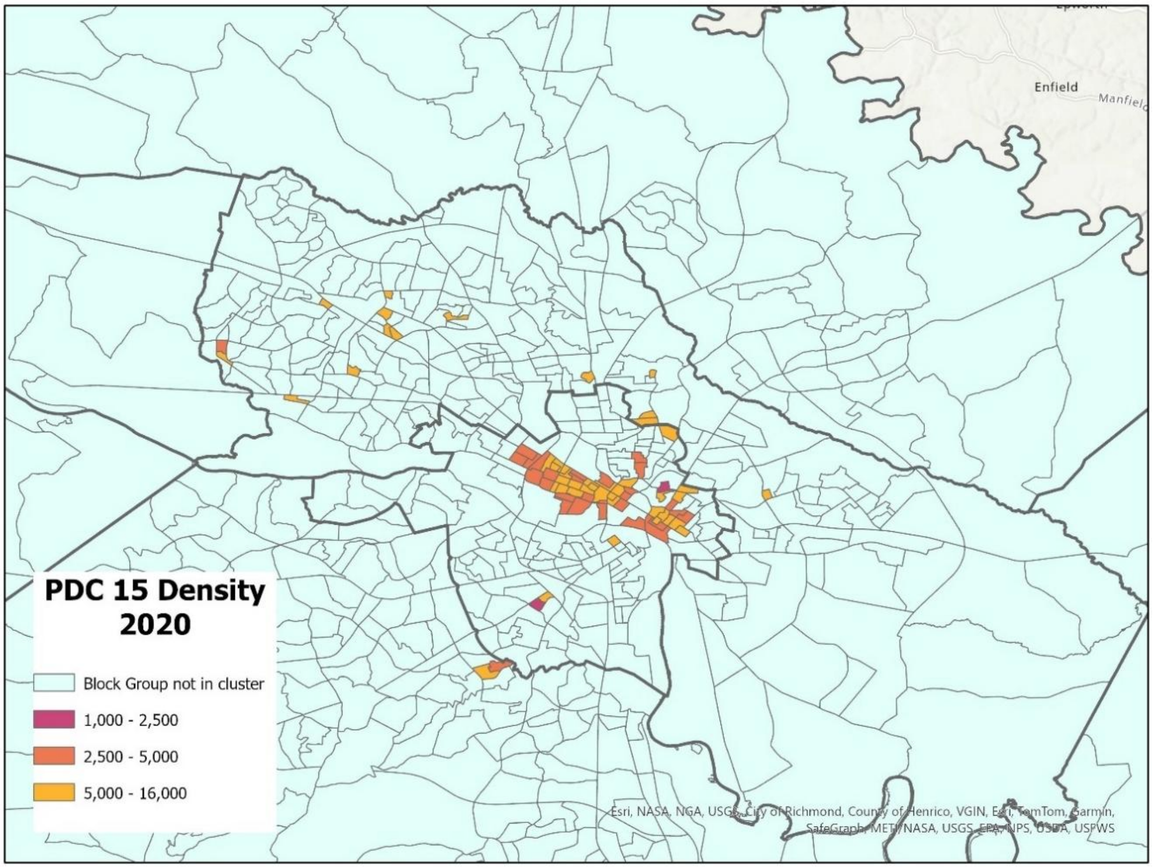

Figure 5. High-Density Clusters of Census Block Groups in Richmond. PDC = planning district commission.

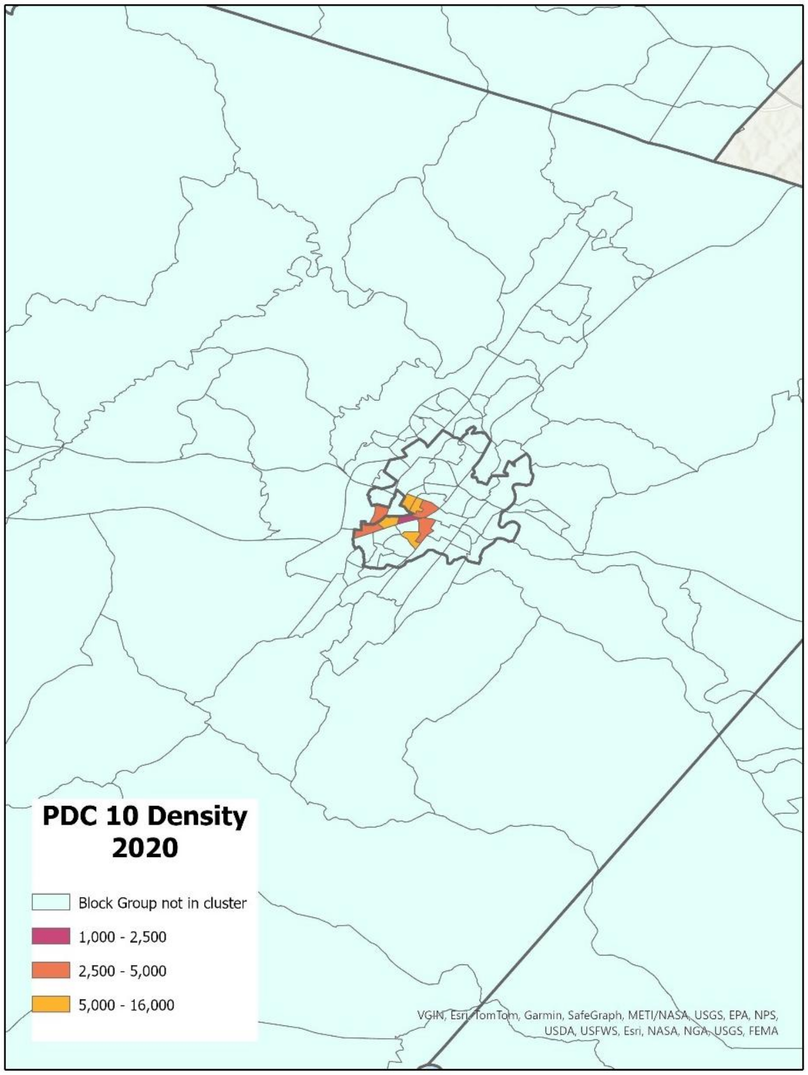

Figure 6. High-Density Cluster of Census Block Groups in Charlottesville. PDC = planning district commission.

For example, according to the estimation results in Table 12a, Woods & Poole's forecasts predict a "hollowing-out" of the urban core in the Hampton Roads Planning District from 2020 to 2040. The total population of the district—and therefore, the average population density—will continue to grow but the high-density urban core of the district around the James River bridge-tunnels will shrink. It would be interesting to see whether detailed census data from 2000 or 2030 corroborate this prediction.

Household Income as a Factor in Automobile Ownership and Dependence on Transit

As noted previously, considerations other than population density contribute to the decision to establish a fixed-route bus service. Furthermore, other considerations influence the travel demand for transit service of all kinds. Household vehicle ownership is one of these other considerations.

Household Income as an Explanatory Factor in Automobile Ownership

AutoInsurance.com, an insurance provider-matching service, published on its website a page of "Car Ownership Statistics 2024" that are derived from a table, U.S. Car Ownership as of 2021, by Income Group, published by the data packaging company Statista (AutoInsurance.com, 2025; Statista, 2025). Table 17 is derived from these statistics.

Table 17. U.S. Car Ownership by Income Group in 2021

Income Bracket (2019 dollars)	Percent of Auto Owners	Percent of U.S. Population
\$0–\$50,000	16%	36%
\$50,000–\$75,000	34%	16%
\$75,000–\$100,000	21%	12%
\$100,000–\$150,000	20%	16%
More than \$150,000	9%	20%

In 2021, approximately 92% of *households* owned motor vehicles. Because an automobile owner may own more than one vehicle, and a household may include more than one automobile owner, these statistics do not permit a straightforward computation of the percentage of people in each income bracket that own cars. However, these figures do imply that the probability of automobile ownership rises steeply between the zero to \$50,000 per year income bracket and the \$50,000 to \$75,000 per year income bracket.

This being the case, tabulating the number and percentage of households in each locality whose income (adjusted for inflation) equals \$50,000 or less per year, at 2019 prices, will imply something about the prevalence of car ownership in the locality. Therefore, it will imply something about the number and percentage of households that are likely to depend for mobility on a vehicle that they do not own personally such as a public transit vehicle, a friend's or relative's vehicle, and so on.

The "Under \$50,000" Cut of the Household Income Distribution across Planning Districts

The maps in Figure 7 show the percentage of households in each planning district whose income equals \$50,000 or less at 2019 prices. The map for 2020 represents the historical statistics, and the map for 2040 represents the Woods & Poole forecasts.

The maps in Figure 8 show the number of households in each planning district whose income equals \$50,000 or less at 2019 prices. Again, the map for 2020 represents the historical statistics, and the map for 2040 represents the Woods & Poole forecasts.

The absolute number of households in the income brackets most likely not to own a car is presumably a more useful statistic for determining the feasibility of a fixed-route transit system. Figure 8 shows that the planning districts with the highest numbers of lower income households are the most heavily urbanized districts. By contrast, Figure 7 shows that the planning districts with the highest percentages of lower income households are clustered in the southern and the southwestern parts of the state.

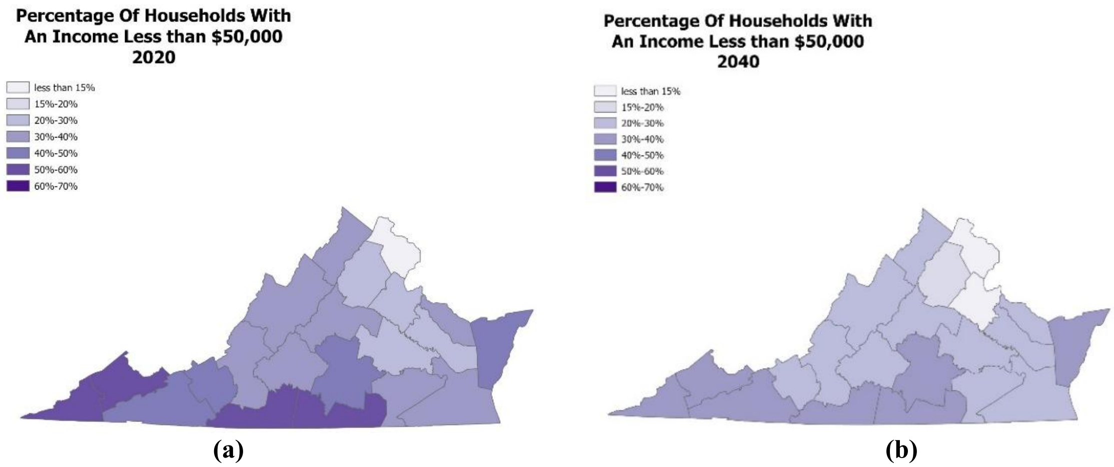

Figure 7. Percentage of Households with Income under $50,000 at 2019 Prices in Each Planning District: (a) In 2020; (b) Forecast for 2040. A district whose percentage equaled *exactly* 20% would be assigned to the "20%–30%" bracket and so on.

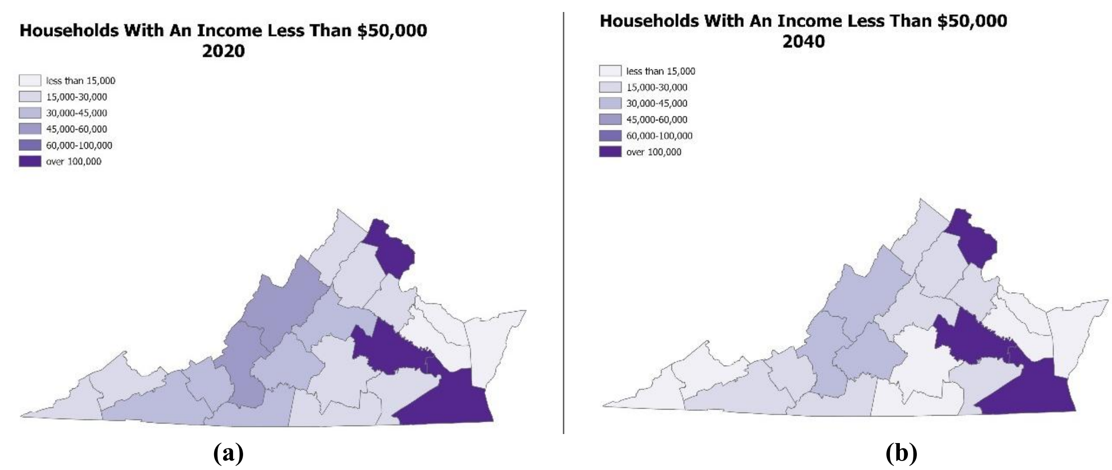

Figure 8. Number of Households with Income under $50,000 at 2019 Prices in Each Planning District: (a) In 2020; (b) Forecast for 2040. A district where the number of households equaled *exactly* 30,000 would be assigned to the "30,000-45,000" bracket and so on.

Household Income as an Explanatory Factor in Electric Vehicle Ownership?

In the VTrans framework, macrotrend 3, Adoption of Electric Vehicles, recognizes four trend trackers. The third of these trackers is Attitude and Preferences for Adoption of Electric Vehicles.

The average electric vehicle has historically required and, at this writing, continues to require a higher up-front purchase cost than the average gasoline-powered vehicle, electric vehicle ownership is likely to skew more toward the upper portion of the income distribution than automobile ownership in general. It is possible that an analogous "high-end" cut of the households in each planning district *above* a certain income threshold would prove a useful indicator of the propensity to own electric vehicles. This is a possible direction for future investigation.

Population and Income as Correlates of Real Estate Market Values

Real estate prices have implications for several dimensions of transport planning. They affect the cost to a transport agency of acquiring right-of-way for construction. They affect housing costs, thereby influencing the tradeoff between the share of housing expenses and the share of transport expenses in total household expenditures. Real estate prices influence the land use patterns, the jobs-housing balance, and the average commute length in a region.

Assessed Real Estate Values as a Function of Population, Income, and Time

The Virginia Department of Taxation does not routinely forecast future average real estate values but does publish annually an analysis of the Assessment-Sales Ratios in each county and city. Each annual edition includes a Table 4 that shows the estimated total market value of real estate in each county and city. Taken as a series, these publications provide a historical record of the estimated value of real estate in each jurisdiction (Virginia Department of Taxation, 2000, 2020).

The researchers compiled two of the VTrans trend trackers that are available in the Woods & Poole dataset: (1) historical estimates and future forecasts of population and (2) historical estimates and future forecasts of personal income. They compiled also the area in square miles of each local jurisdiction, not a trend tracker but a datum also available in the Woods & Poole dataset and in numerous other sources. Using the estimated total market values and the land areas, the researchers constructed a historical time series of average market value per square mile of real estate in each county and city for 2000 and 2020. The investigators also constructed a historical and forecast future time series of (1) population per square mile and (2) personal income per capita in each county and city for 2000, 2020, 2030, and 2050.

The researchers estimated a regression equation. The dependent variable was the historical values of the estimated total market value of real estate in each county and city in 2000 and 2020 (Virginia Department of Taxation, 2000, 2020). The independent (explanatory) variables were as follows: (1) the historical values of population per square mile in 2000 and 2020; (2) the historical values of personal income per capita in 2000 and 2020; and (3) the year number for each record in the regression dataset, either 2000 or 2020. All variables except the year number were converted to natural logarithms.

$$\ln(REValue_{ij}) = a_0 + a_1*Year_j + a_2*\ln(Pop_{ij}/Area_i) + a_3*\ln(Inc_{ij}/Pop_{ij}) + \varepsilon_{ij}, \qquad \text{(Eq. 1)}$$

Where:
$REValue_{ij}$ = estimated total market value of real estate in locality i in year j.
$Area_i$ = area of locality i in square miles.
Pop_{ij} = population in locality i in year j.
Inc_{ij} = total personal income in locality i in year j.
ε_{ij} = an unobserved error term specific to locality i in year j.

Table 18 reproduces the results of the regression.

Table 18. Regression: Estimated Fair Market Value as a Function of Three Explanatory Variables[a, b]

Independent Variable	Point Estimate of Coefficient	Standard Error of Estimate	t-statistic	One-Tailed P-Value
Constant term	− 1.598450	0.602285	− 2.653976	0.004474
Income per capita ($)	1.222772	0.058550	20.884236	< 0.000001
Pop. Density (pers/mi^2)	0.958506	0.008763	109.381034	< 0.000001
Year	0.020445	0.001742	11.736510	< 0.000001

Pop. = population; [a]Degrees of freedom = 130; [b] R-squared = 0.982824.

The coefficient on the year number is the easiest to interpret. Each year augmented the true market value in current-year dollars by about 2 percentage points. The coefficients on the other two variables imply that a one-percent increase in income per capita would be associated with an increase in real estate prices of 1.2 to 1.25 percentage points. In contrast, an increase in population density of one percent would be associated with an increase in real estate prices of slightly less than one percentage point.

Forecasts of Future Assessed Real Estate Values

The researchers applied the model parameters estimated in the regression to the forecasts of personal income per capita and population per square mile derived from the Woods & Poole dataset to forecast the average value per square mile of real estate in each jurisdiction in Virginia in 2030 and 2050. They then aggregated the historical averages and the future projected averages to obtain weighted average values per square mile for each planning district in Virginia. Figures 9 and 10 show the historical averages for 2000 and 2020, and the projected averages for 2030 and 2050 for each of Virginia's planning districts. The less expensive and more expensive planning districts are charted separately to allow the less expensive districts to be charted at a finer level of detail. The Thomas Jefferson Planning District appears in both figures for purposes of comparison.

Prospects for Further Investigation

The Virginia Department of Taxation does not forecast future average real estate values. The previous exercise demonstrates that one can combine the historical estimates of average real estate values with the purchased population and income estimates to obtain a forecast of future average real estate values. As future editions of the Assessment Sales Ratio studies are published, it will be possible to assess the accuracy of these forecasts.

The regression equation, which the researchers estimated, simple as it was, explained more than 98% of the variation in the average real estate values in Virginia's cities and counties. Quite possibly the addition of even one more explanatory variable, or a minor tweak to the functional form, could make the "fit" of the model appreciably tighter than it already is.

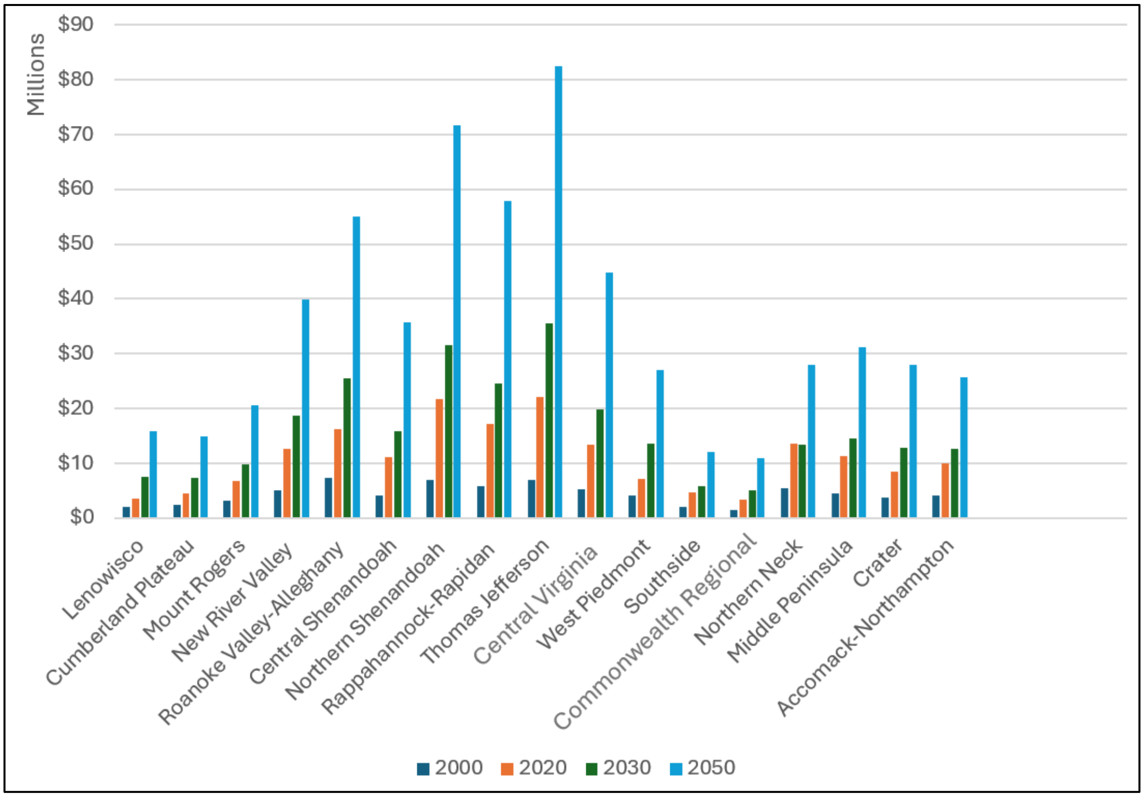

Figure 9. Historical and Projected Average Values per Square Mile of Real Estate in the 17 Least Densely Settled Planning Districts

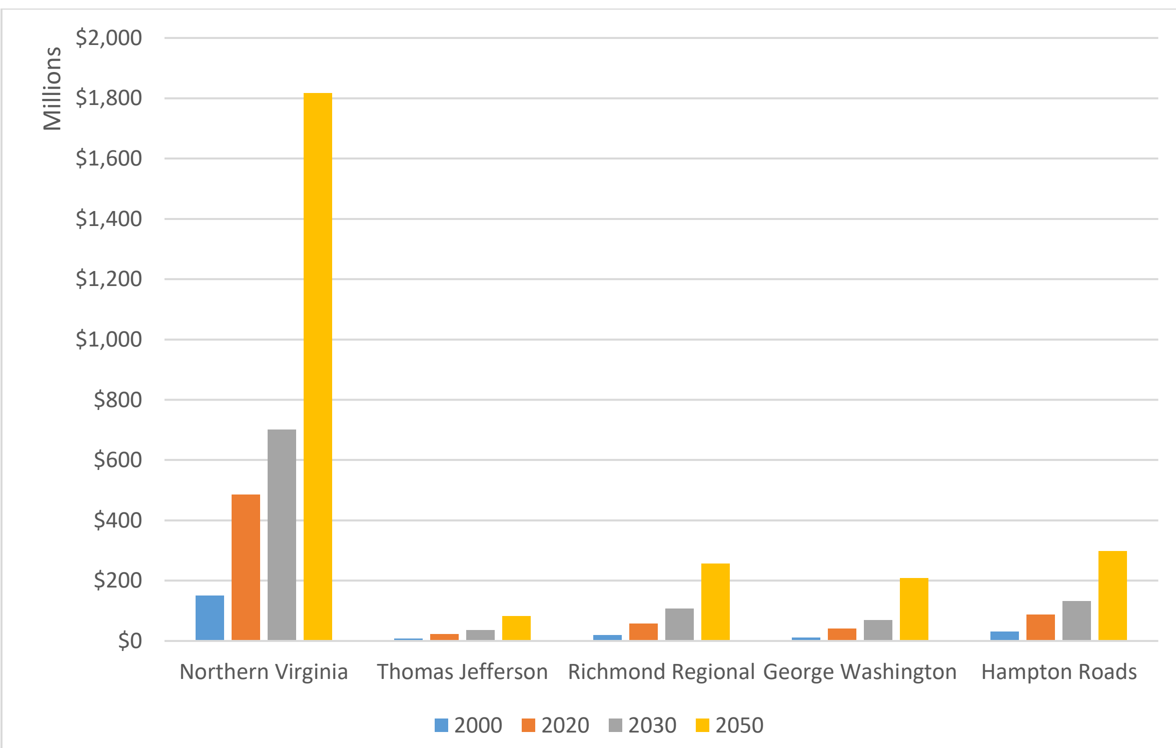

Figure 10. Historical and Projected Average Values per Square Mile of Real Estate in The Five Most Densely Settled Planning Districts

Population and Employment Forecasts as Proxies for Jobs-Housing Ratio Forecasts

The jobs-housing ratio is a familiar metric to transport planners. Planners consider the jobs-housing ratio, computed at the census tract (or census block group or census block) level, to be one of the factors that influences the mode choice of travelers who live in the tract and the commute distance of workers who live in the tract.

Census-tract-level forecasts of jobs and housing are rarely available. Would county- and city-level forecasts of employment and population, those produced by Woods & Poole for example, reveal any trends that have importance for regional commuting patterns? The researchers computed the ratio of employment to population in each county and city in the Commonwealth of Virginia for every year covered in the Woods & Poole dataset, from 1969 to 2060.

The statewide average ratio of employment to population shows many fluctuations during 1969 through 2023, mirroring the historical economic expansions and contractions. Nonetheless, the ratio displays a general upward trend of 0.536% per year. Woods & Poole forecast that this trend will continue in the years from 2023 to 2060 at the rate of 0.434% per year.

Figures 11 through 14 display color-coded maps of the ratio in each county and city as of 2000, 2020, 2030, and 2050. These statistics were historical statistics for 2000 and 2020 and forecasts for 2030 and 2050. These statistics are expressed as a proportion of the statewide average ratio from 2021 to 2022.

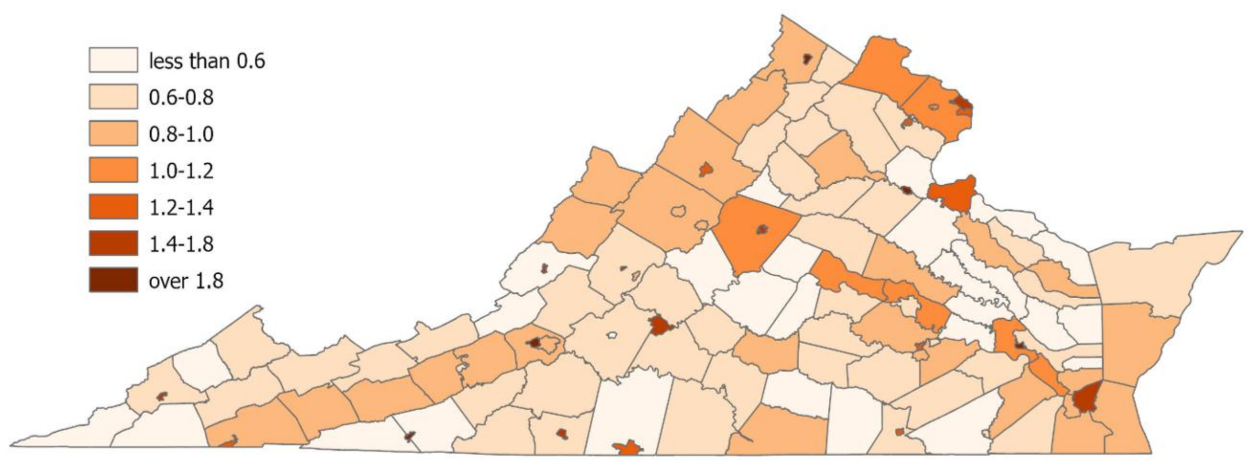

Figure 11. Employment-to-Population Ratio in Each County and City in 2000 as a Proportion of the Statewide Average Ratio from 2021 to 2022. A county or city whose ratio equaled *exactly* 0.6 would be assigned to the "0.6–0.8" bracket and so on.

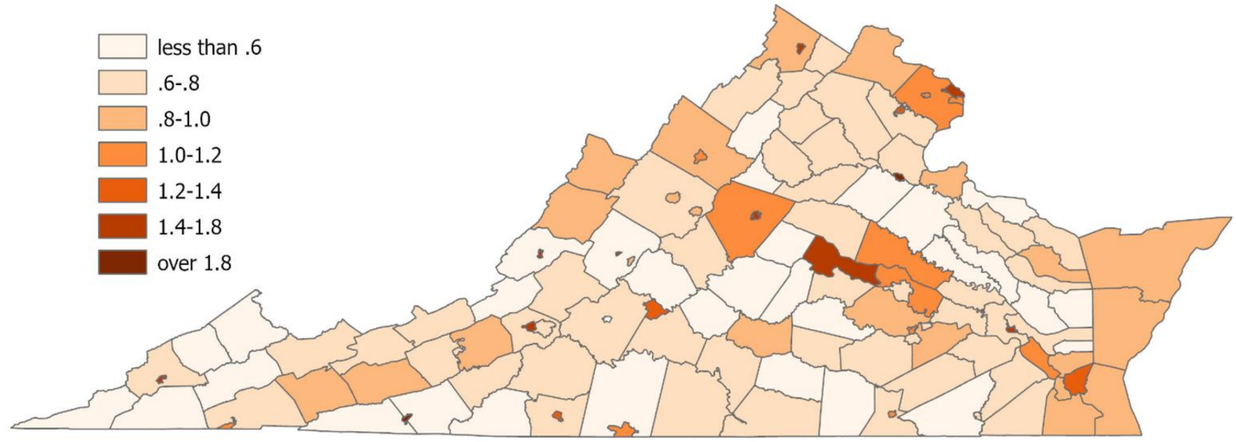

Figure 12. Employment-to-Population Ratio in Each County and City in 2020 as a Proportion of the Statewide Average Ratio from 2021 to 2022. A county or city whose ratio equaled *exactly* 0.6 would be assigned to the "0.6–0.8" bracket and so on.

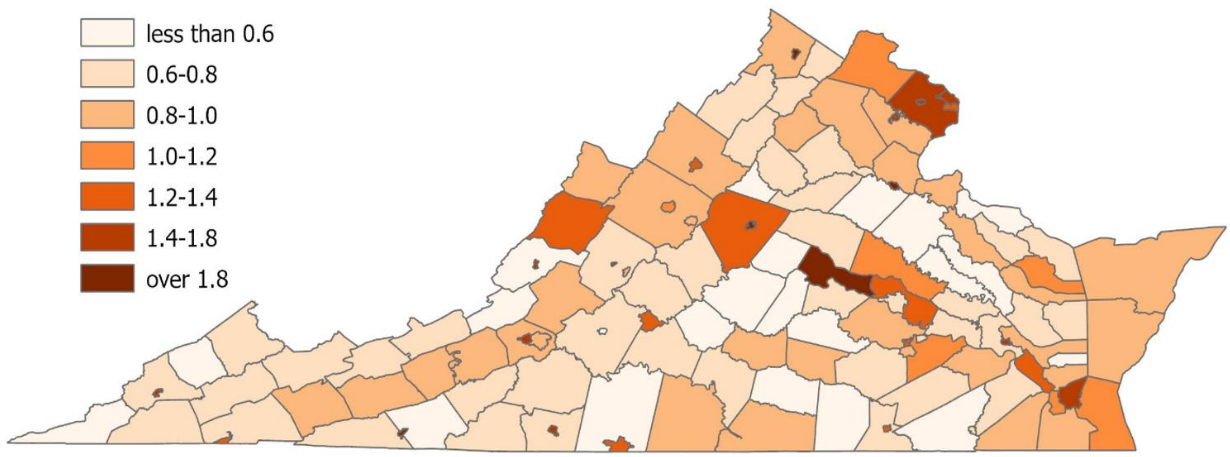

Figure 13. Employment-to-Population Ratio in Each County and City Forecast for 2030 as a Proportion of the Statewide Average Ratio from 2021 to 2022. A county or city whose ratio equaled *exactly* 0.6 would be assigned to the "0.6–0.8" bracket and so on.

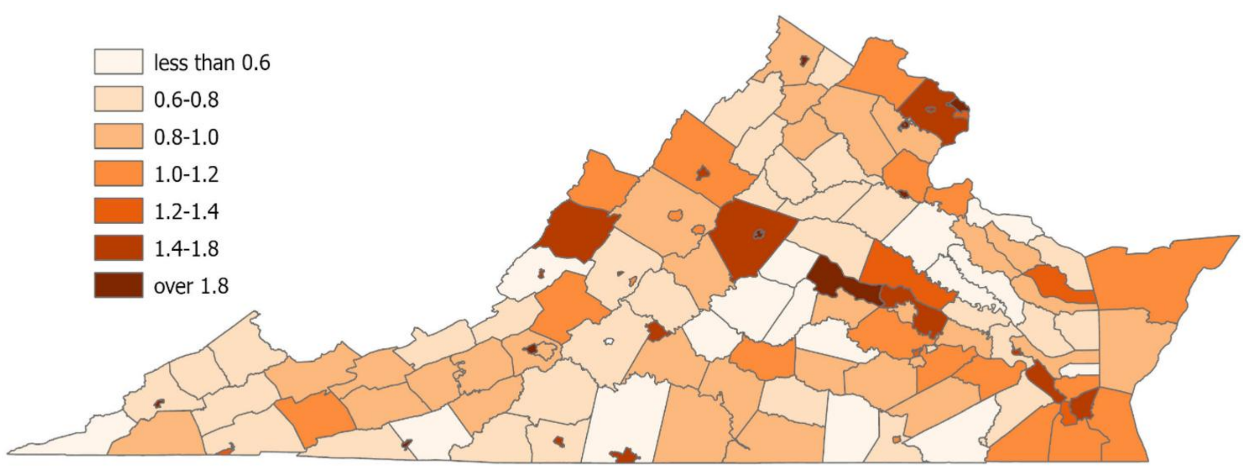

Figure 14. Employment-to-Population Ratio in Each County and City Forecast for 2050 as a Proportion of the Statewide Average Ratio from 2021 to 2022. A county or city whose ratio equaled *exactly* 0.6 would be assigned to the "0.6–0.8" bracket and so on.

One trend, evident in the employment and population data viewed separately, is that the number of jobs has grown at a faster rate than the population and is forecast to continue to grow at a faster rate. The appearance of more dark shades in the maps for later years reflects this trend.

The tendency for the counties and cities along the I-81 corridor to have a relatively high ratio of employment to population, compared with the ratio in the neighboring counties through which I-81 does not pass, is noticeable in year 2000 and is forecast to persist. Counties and cities along the I-64 corridor show traces of a similar tendency, although the tendency along I-64 is less distinct.

Another noticeable pattern is that most independent cities—the jurisdictions of smaller area on the maps—generally exhibit employment-to-population ratios as high, or higher, than those in nearby jurisdictions. The cities of Richmond, Petersburg, and Hopewell are notable exceptions to this pattern. The city of Alexandria is forecast to become another such exception in the out years 2030 and 2050.

The reader will understand that the trends these Woods & Poole forecasts reveal, like the visions that the Ghost of Christmas yet to Come shows to Ebenezer Scrooge in Charles Dickens's novella *A Christmas Carol*, are things that *may* come to pass, not things that *must* come to pass. The trends can be perhaps best understood as indications of patterns that may be expected in the absence of policy changes that steer them in a different direction.

The researchers did not retrieve data on the average commute length for residents in each county and city. To tabulate the average commute length in parallel with the employment-to-population ratio to see if a correlation exists would be an interesting next step.

Summary of Findings

Tasks 1, 2, and 3 each yielded a set of findings.

Findings from Task 1

- *During the 20-year period from 2020 to 2040, the total population of the Commonwealth of Virginia is forecast to grow at a rate of 0.688% per year.* During the same period, the populations in the nine VDOT construction districts are forecast to grow at rates between –0.179% per year in Bristol and +1.215% per year in Fredericksburg. The populations in the 21 planning districts are forecast to grow at rates between –0.395% per year in the Cumberland Plateau Planning District) and +1.500% in the George Washington Planning District.

- *During the 20-year period from 2020 to 2040, the population aged 65 and older is forecast to grow at a rate of 2.018% per year, a higher rate than the rate of growth of the total population*. In the VDOT construction districts and the planning districts, too, the growth rate of the population aged 65 and older is forecast to be higher than the growth rate of the total population in every planning district. This pattern presumably reflects increases in longevity from one age cohort to the next and decreases in fertility from one age cohort to the next.

- *In the historical census years 2010 and 2020, Woods & Poole's population estimate differs from the Cooper Center's population estimate by less than 2% in every planning district. In the future census year 2030, Woods & Poole's forecast differs from the Cooper Center's forecast by as much as 12% in some districts, with the Cooper Center forecast usually being the higher of the two.*

- *During the 20-year period from 2020 to 2040, total employment in the Commonwealth of Virginia is forecast to grow at a rate of 0.864% per year.* This growth rate is higher than the forecasted population growth rate of 0.688% per year. Taken together, these two rates imply a forecast that labor force participation will increase at the rate of about 0.176% per year.

- *Four different calculations measured each economic sector's dependence on goods movement based on the sector's purchases of intermediate goods and services from the transportation and warehousing sector. Each of the four calculations resolved three clear groups. The top group always comprised the same three sectors—the wholesale trade sector, the retail trade sector, and the transportation and warehousing sector*. The sum of employment in these three sectors would be one candidate for the Number of Jobs in Goods Movement Dependent Industries, the fourth trend tracker of VTrans macrotrend 5, Growth in E-Commerce (OIPI, 2025a). A sum that included the employment in additional sectors further down the list could also be a candidate. Sector-by-sector employment totals are available in the Woods & Poole dataset that Virginia currently purchases to track other trends in the VTrans framework.

- *Exogenous shocks to the U.S. economy, possibly including a technological shock attendant upon the adoption of large language models (LLMs) and other forms of advanced AI, are not reflected in long-term employment forecasts*. Starting with employment and earnings, detailed forecasts reflect gradual historical change rather than the effects of unexpected events. Nonetheless, they can be adjusted to incorporate the impacts of exogenous information or assumptions on employment, which is the foundation of the detailed Woods & Poole projections.

- *During the 20-year period from 2020 to 2040, the total personal income in the Commonwealth of Virginia is forecast to grow at a rate of 2.212% per year.* During the same period, the total personal incomes in the nine VDOT construction districts are forecast to grow at rates between +1.141% per year in Bristol and +2.738% per year in Fredericksburg. The total personal incomes in the 21 planning districts are forecast to grow at rates between –0.908% per year in the Cumberland Plateau Planning District and +3.142% in the George Washington Planning District. The forecast growth rates of personal income are positive in every district and higher than the forecast growth rates of population in every district. Taken together, these two rates imply a forecast that personal income per capita will grow at a rate of about +1.524% per year.

- *Personal income and household income, two of the time series available in the Woods & Poole dataset that Virginia currently purchases to track the trends identified in the VTrans framework, both have potential transport planning uses.* This study experimented with using household income brackets as a proxy for the extent of automobile ownership in each planning district. This study experimented with personal income, along with population, in a model that forecasts land values, an important factor in right-of-way costs. Like population and employment, income is one of the trend trackers of VTrans macrotrend 10, Population and Employment Shift.

- *The changes in demographic indicators—in per capita income, for instance—that sometimes accompany residential turnover can present challenges for transport policies that consider the location of disadvantaged populations when choosing among transport investments*. The longer the transport investment timeline, the more likely that demographic change will occur in the neighborhood of the investment. The greater the expected economic and land use impacts of the transport investment, the more likely that demographic change will occur in the neighborhood of the investment. Demographic change can cause the disadvantaged population to move out of the way of the investment, as it were. On the other hand, the higher the geographic scale at which transport policy aggregates the demographic indicators of "disadvantage," the smaller the risk that demographic change will cause one of the indicators to drop below the policy threshold.

Findings from Task 2

- *Analysis of the differences between Woods & Poole's forecast of a population statistic some years in advance and Woods & Poole's later finalized estimate of the same population statistic as a historical fact unsurprisingly revealed that a forecast made several years in advance tends to be less accurate than a forecast made only a few years in advance*. The one set of forecasts made at a lead length of 8 years varied from the finalized estimates (revealed later) with a root mean squared difference of 10.20%. The two sets of forecasts made at a lead length of 4 years varied from the finalized estimates with root mean squared differences of 3.19% and 6.68%. The four sets of forecasts made at a lead length of zero years (at zero years, an estimate is not finalized) varied from the actual values with root mean squared differences that ranged from 0.27% to 2.46%.

- *The analysis revealed that the amount of discrepancy in a set of forecasts 4 years in advance—or 3 or 2 or 1 or zero years in advance—varied from one year's set to another year's set. Whether quantified by the standard deviation or by the root mean squared difference, the amount of* noise *in the forecasts was not always the same*. This finding was also not surprising. It means that some future years hold bigger surprises in store than others, and bigger future surprises add more error to the forecasts.

- *The differences between Woods & Poole's employment forecasts and their later finalized estimates exhibited patterns similar to those that the population forecasts exhibited; however, the differences tended to be bigger*. The one set of forecasts made at a lead length of 8 years varied from the actual values (revealed later) with a root mean squared difference of 18.26%. The two sets of forecasts made at a lead length of 4 years varied from the actual values with root mean squared differences of 8.72% and 15.38%. The four sets of forecasts made at a lead length of zero years (at zero years, an estimate is not finalized) varied from the actual values with root mean square differences that ranged from 2.63% to 4.08%.

- *The differences between Woods & Poole's personal income forecasts and their later finalized estimates also exhibited patterns similar to those that the population forecasts exhibited; however, again the differences tended to be bigger*. The one set of forecasts made at a lead length of 8 years varied from the actual values (revealed later) with a root mean squared difference of 14.77%. The two sets of forecasts made at a lead length of 4 years varied from the actual values with root mean squared differences of 7.37% and 15.38%. The four sets of forecasts made at a lead length of zero years (at zero years, an estimate is not finalized) varied from the actual values with root mean squared differences that ranged from 4.26% to 8.85%.

- *In the period for which they were retrievable, the Woods & Poole forecasts overestimated future population, employment, and personal income more often than they underestimated it*. The researchers believe this result is a peculiarity of the period from which the forecasts were retrieved, not a bias in the Woods & Poole model.

- *Measurement of the amount of uncertainty in longer range forecasts would add to the utility of the previous findings*. Transport planners customarily forecast travel demand 20 to 40 years into the future. Bhairavabhatla et al. (2020), working on a previous VTrans update, compared a pair of independent forecasts of the populations in 14 jurisdictions in Northern Virginia in the year 2045. These forecasts, whose accuracy cannot yet be tested, were made in 2017 and 2018. Bhairavabhatla et al. (2020) found that the forecasts differed *from one another* with a root mean squared difference of 22.40%.

Findings from Task 3

- *A relatively simple computation method based on 2020 population densities at the county and city levels does a reasonably good job of predicting the size and population of the area in each planning district that is well suited to fixed-route bus service, according to the* Transit Capacity and Quality of Service Manual (NASEM, 2013). The middle tier of eight planning districts, where the suitability of fixed-route transit is most in question, happens to be the group of districts that the method fits worst. The validation used 2020 census data. Further study of the method, using census data from another census year—2000, 2010 or later, or 2030—may establish whether block group-level census data validate the trends that appear when the computation method is applied to county- and city-level data.

- *A breakdown of the number of households in each county and city into income brackets shows some potential as a measure to proxy for automobile ownership and transit dependence.* The tabulation of the households below a threshold household income level of $50,000 per year at 2019 prices showed patterns and trends for the period 2000 through 2040. A possible direction for future study would be the analogous use of a breakdown into income brackets as a measure to proxy specifically for electric vehicle ownership.

- *A simple model using population per square mile, personal income per capita, and the year number does a reasonably good job of forecasting changes in land values at the county and city level*. Land values are an important determinant of VDOT right-of-way acquisition costs.

- *Compilation of the ratio of employment to population at the county and city level reveals some expected geographic patterns with respect to the location of interstate highways and the importance of interstate highways for freight movement*. This observation provides some preliminary evidence that the trends in the employment/population ratio, which can be inferred from the forecasts of future employment and population, may have value for planners. Comparing the county- and city-level employment ratios with estimates of average commute time or average commute distance, which would provide further corroboration, is a possible direction for future study.

CONCLUSIONS

- *Localities can use the VTrans forecasts for several planning applications that may be of interest to them*. Four applications illustrated herein are (1) using population forecasts to determine if and when density will increase to a level sufficient to support fixed-route bus service, (2) using income forecasts to estimate households that will not have access to a vehicle, (3) using income and population forecasts to estimate changes in right-of-way costs, and (4) using employment and population forecasts to forecast changes in jobs-housing balance.

- *Employment in three economic sectors—the wholesale trade, the retail trade, and the transportation and warehousing sectors—is a viable way to define the VTrans trend tracker Number of Jobs in Goods Movement Dependent Industries*. Four different calculations ranked each sector's dependence on goods movement by its purchases of intermediate goods and services from the transportation and warehousing sector, and the top group always comprised these three sectors.

- *Personal income and household income, two of the time series available in the Woods & Poole dataset that Virginia currently purchases to track the trends identified in the VTrans framework, both have potential transport planning uses.* First, the fraction of households in lower household income brackets is a proxy for the extent of automobile ownership in each planning district. Personal income per capita and population density can be used to model right-of-way costs. Like population and employment, income is one of the trend trackers of macrotrend 10, Population and Employment Shift.

- *Population forecasts tend to have smaller errors than employment and income forecasts, and forecasts of more remote years tended to have larger errors.* Woods & Poole generate forecasts of future population, employment, and personal income statistics for 105 regions in

Virginia—each consisting of one county, one city, or one county plus one or two small cities—which are defined by BEA for statistical purposes and used likewise by Woods & Poole. Population forecasts generated during 2014 to 2022 showed root mean squared differences between the forecasts and the finalized estimates (2 years ex post) ranging from less than 1% to 10.20%, with forecasts of more remote future years (e.g., 6 to 8 years away) tending to have larger errors than forecasts of closer impending future years (e.g., 1 to 2 years away). Employment forecasts generated during 2014 to 2022 showed root mean squared differences between the forecasts and the finalized estimates ranging from 2.63% to 21.18%. This pattern was much "noisier" than the pattern in the population forecasts. The personal income forecasts exhibited performance quantitatively similar to the performance of the employment forecasts. The variances, measured with respect to Woods & Poole's own finalized estimates, are perhaps best understood not as Woods & Poole's errors in forecasting the final official Census Bureau or BEA statistic but as a representative illustration of the degree of uncertainty that may be expected in the evolution of any professional estimate.

- *Changes in demographic attributes, such as income, sometimes accompany residential turnover, presenting challenges for transport policies that consider the location of disadvantaged populations when choosing transport investments*. This residential turnover is increased for transport investments that have either longer timelines or larger economic and land use impacts. The instability that this residential turnover entails will tend to be diluted if one aggregates demographic indicators of "disadvantage" to coarser geographic scales (e.g., census tracts rather than blocks).

RECOMMENDATIONS

1. *OIPI should consider the sum of employment in the wholesale trade, the retail trade, and the transportation and warehousing sectors as a candidate for the Number of Jobs in Goods Movement-Dependent Industries, one of the trend trackers of VTrans macrotrend 5, Growth in E-Commerce.*

2. *OIPI should consider personal income and/or household income as candidates for the Income trend tracker, one of the trend trackers of macrotrend 10, Population and Employment Shift*.

3. *OIPI and VDOT's Transportation Mobility Planning Division should make the information about the differences between the earlier forecasts and the later historical values in successive editions of the Woods & Poole dataset available as supplementary information on a website where the population, employment, and income trend trackers are available or on a website where the use of these data is discussed*.

IMPLEMENTATION AND BENEFITS

The researcher and the technical review panel (listed in the Acknowledgments) for the project collaborate to craft a plan to implement the study recommendations and determine the benefits of doing so. This process is to ensure that the implementation plan is developed and approved with the participation and support of those involved with VDOT operations. The implementation plan and the accompanying benefits are provided here.

Implementation

Regarding Recommendation 1, OIPI will invite a member of the research team to present a summary of this study's findings, conclusions, and recommendations at a quarterly Metropolitan Planning Organization meeting by the end of 2027. This presentation will enable the audience to learn how the sum of employment from the wholesale trade, the retail trade, and the transportation and warehousing sectors could serve as the Number of Jobs in Goods Movement-Dependent Industries trend tracker for Growth in E-Commerce.

Regarding Recommendation 2, OIPI will invite a member of the research team to present a summary of this study's findings, conclusions, and recommendations at a quarterly Metropolitan Planning Organization meeting by the end of 2027—the same meeting noted for Recommendation 1. This presentation will enable the audience to learn how personal income and/or household income could serve as the Income trend tracker for Population and Income Shift.

Regarding Recommendation 3, VDOT's Transportation Mobility Planning Division will insert a reference to Tables 13a, 13b, and 13c of this report as an informational item in the Virginia Travel Demand Modeling Policies and Procedures Manual *by the end of 2027* (Cambridge Systematics, 2020).

Regarding Recommendation 3, OIPI will insert a reference to Tables 12a, 12b, 12c, 13a, 13b, 13c, 14a, 14b, and 14c of this report as a footnote or an informational item on the web page that discusses the trend trackers for macrotrend 10, Population and Employment Shift by the end of 2027. One description of the trend trackers was available at OIPI (2025) on November 18, 2025.

Benefits

The researchers already submitted files to OIPI in the desired format that contain tables of the four established trend trackers: (1) total population; (2) population aged 65 and older; (3) total employment; and (4) employment in the professional and technical services sector. These data are presumed to add the same unquantifiable value to CTB's deliberations that they have added in past years.

Recommendations 1 and 2 propose the provisional adoption of a specific employment statistic and a specific income statistic to represent two additional trend trackers within the established VTrans framework. If implemented, these steps will add to the set of data that informs the CTB's deliberations. Recommendation 3 proposes the dissemination of information about the margin for error in two established trend trackers and in one proposed trend tracker. If implemented, this step will enhance the user's understanding and handling of the trend trackers, whether the user be a member of the CTB or another organization.

ACKNOWLEDGMENTS

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