DELAWARE VALLEY REGIONAL PLANNING COMMISSION

ADR21014 | January 2023

Analytical Data Report

Population and Employment Forecasts
2015–2050

DELAWARE VALLEY data

The Delaware Valley Regional Planning Commission is the federally designated Metropolitan Planning Organization for the Greater Philadelphia region, established by an Interstate Compact between the Commonwealth of Pennsylvania and the State of New Jersey. Members include Bucks, Chester, Delaware, Montgomery, and Philadelphia counties, plus the City of Chester, in Pennsylvania; and Burlington, Camden, Gloucester, and Mercer counties, plus the cities of Camden and Trenton, in New Jersey.

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DELAWARE VALLEY dvrpc REGIONAL PLANNING COMMISSION

DVRPC's vision for the Greater Philadelphia Region is a prosperous, innovative, equitable, resilient, and sustainable region that increases mobility choices by investing in a safe and modern transportation system; that protects and preserves our natural resources while creating healthy communities; and that fosters greater opportunities for all.

DVRPC's mission is to achieve this vision by convening the widest array of partners to inform and facilitate data-driven decision-making. We are engaged across the region, and strive to be leaders and innovators, exploring new ideas and creating best practices.

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Background

This analytical data report (ADR) documents the population and employment forecasts developed for the nine-county Greater Philadelphia region through the year 2050 and the process by which they were developed for the Delaware Valley Regional Planning Commission's (DVRPC's) *Connections 2050* Long-Range Plan. For future reference, relative to other forecasts, this product is known as the 2050 v1.0 population and employment forecasts.

Purpose

Population and employment forecasts are a critical component of long-range land use and transportation planning. Beyond being useful to a variety of DVRPC studies and analyses, forecasts are a federal requirement under 23 CFR chapter 1, subchapter E, section 450.324(e), which states: [1]

> *The [metropolitan planning organization (MPO)], the State(s), and the public transportation operator(s) shall validate data used in preparing other existing modal plans for providing input to the transportation plan. In updating the transportation plan, the MPO shall base the update on the latest available estimates and assumptions for population, land use, travel, employment, congestion, and economic activity. The MPO shall approve transportation plan contents and supporting analyses produced by a transportation plan update.*

This forecast was required for use in the federally mandated air quality conformity analysis conducted for the Fiscal Year (FY) 2022 New Jersey Transportation Improvement Program (TIP) update and the *Connections 2050* long-range plan. Both population and employment forecasts were formally adopted by the DVRPC Board on June 24, 2021 and will serve as a key component of DVRPC planning and travel modeling studies and analysis until the next forecasts are adopted. Forecasts are adopted for total population and total employment at the municipal level in the eight counties surrounding Philadelphia, and by the 18 planning districts within Philadelphia. The 2015 base year of the prior DVRPC forecast remained the same but the horizon year was extended to 2050. Forecasts were adopted for each five-year increment between base and horizon years: 2020, 2025, 2030, 2035, 2040, and 2045.

The DVRPC population and employment forecasts are not meant to be aspirational or reflect an implementation of a growth vision for the region. They strive to reflect a plausible outcome for regional change in a 30-year period, with only current trends and knowledge of potential future trajectories from which to draw. As the basis for travel model future demand and the transportation funding decisions informed by modeling, the agency acknowledges no forecast is a crystal ball into what will transpire but uses data available and sound behavioral observations to best approximate reasonable socioeconomic and land use outcomes.

What's in this Report

This ADR is divided into two parts. The first section documents the new process DVRPC developed for this update. The second part summarizes the forecast results. For those interested in the results only, skip ahead to Part II. Part I summarizes the method applied for the previous forecast; the newly formed Socioeconomic and Land Use Analytics Committee, comprising county planning partner staff who were involved in all steps of the forecast; the development of the UrbanSim land use model; and the creation of a development pipeline to feed into UrbanSim. Part I further details how UrbanSim operates with agent-based synthetic population, probabilities based on explanatory variables, regional control totals, submodels for location choice, real estate pricing, residential and commercial developer location choice, and supply side restrictions that simulate zoning. Appendix A details

1 Code of Federal Regulations, Title 23, Chapter 1, Subchapter E, Section 450.324(e) www.ecfr.gov/current/title-23/chapter-I/subchapter-E/part-450/subpart-C/section-450.324

municipal and City of Philadelphia planning district population forecasts for every five years from 2020 to 2050. Appendix B contains municipal and Philadelphia planning district employment forecasts for every five years from 2020 to 2050. Appendix C documents additional UrbanSim development and configuration information. Appendix D summarizes how base year employment data was developed. Appendix E shows survey results from local developers and municipal officials that identify how they see factors influencing regional development decisions. Finally, Appendix F identifies all the acronyms used in this report.

Timing of Forecast Effort and Implications

Meeting requirements to prepare this forecast in time for air quality conformity analysis meant that a forecasted 2020 population would be adopted shortly before the release of the already delayed 2020 Decennial Census release of total population and other metrics. In the absence of a decennial count, the U.S. Census Bureau's own annual estimates of population by county and municipality were used for a 2015 base year population and later a 2019 base year population. It was the Bureau's underestimation of population totals in their estimates, and thus a starting point well short of conditions reflected in the decennial count, that created a low 2020 population forecast relative to the 2020 Census. For those who are not required to use an adopted forecast for analysis involving future growth, until DVRPC produces a new population forecast from a 2020 Census base, it is recommended to take the change of population forecasted from 2020 to 2050 and apply it to the 2020 Census's population totals.

In addition, the pandemic-induced recession experienced during the forecasting process also played into the general outlook on what was plausible in the nearer and longer-term future for population and employment.

Accessing Forecast Data

Data from the 2050 v1.0 forecasts are visualized and downloadable at various geography levels via the following resources:

- An interactive webmap with municipal/district and county-level charts: Municipal and County-Level Population and Employment Forecasts, 2015-2050.
- Downloadable tables and GIS features at county, municipal/district, and TAZ levels: DVRPC Data Catalog.
- Downloadable county and municipal/district tables with chart visualization: DVRPC Data Navigator.

For requests of variables beyond total population and employment used in the forecast process, please see the staff contact in this report.

PART I:

Connections 2050 Forecast Process

Part I of this report reviews the previous population and employment forecasts, and then reviews many of the enhancements made to the forecasting process for *Connections 2050*. These enhancements include the formation of a new Socioeconomics and Land Use Analytics Committee, the development of a new UrbanSim land use model, and a development pipeline to feed into the UrbanSim model.

Previous Forecast

DVRPC last adopted forecasts for the 2015 to 2045 period in July 2016 for population and October 2016 for employment. These efforts are explained in further detail in ADR022 for population and ADR023 for employment. Prior methods focused solely on creating total population and total employment estimates for counties and municipalities/planning districts for base, horizon, and interim five-year increments.

DVRPC staff met individually with each county planning partner at the outset and presented three different population estimates based on an age-cohort model, or use of either the prior forecast's county distributions or growth rates. For each of these, a method was applied to disaggregate each county's municipalities or planning districts, based largely on carrying forward the prior forecast's assumptions. Using their knowledge of local trends and discussions of future development projects and plans, county staff contacts reviewed their county and municipal/district results. Then they either chose which they felt were most plausible or presented other outcomes that they felt were more likely to occur. The agreed upon forecasts were then adopted by the DVRPC Board.

Employment forecasting began only after the population forecasts were finalized. It began with the clean-up of purchased proprietary base employment data. From that, county employment growth was generated by applying county population growth rates due to labor force growth's relationship to employment growth. Municipal and district employment forecasts were determined largely by carrying forward prior forecast assumptions and consulting county staff on results. Counties then proposed edits as they saw fit, based on local knowledge and expertise.

Former Post-Adoption Zonal Allocation Method

After each 2045 forecast was adopted, DVRPC's travel demand modeling staff had to disaggregate the municipal forecast into smaller geographies known as travel analysis zones (TAZs, or zones) and into many more socioeconomic variables of population types, household attributes, and employment sectors for each zone. This zonal allocation is necessary to run the travel demand model in order to produce air quality conformity results, and analyze other projects required to adhere to board-adopted municipal population and employment forecast totals. In the absence of information considered by DVRPC staff and county partners during the forecasting process, allocation work often defaulted to uniform application of municipalities' growth rates to the zones within it. This ignored the reality on the ground that some zones were already being built out and others being candidates for future growth.

Attention to variations in zonal growth rates were most often applied in locations with plans for large, known projects or transformative master plans. Examples of special attention areas for zonal allocation were plans for Philadelphia's Navy Yard, Delaware River Waterfront, Schuylkill Yards, and 30th Street Station Area in University City, and the Naval Air Station Joint Reserve Base Willow Grove (NASJRB Willow Grove) Redevelopment Plan in Montgomery County. Staff from DVRPC's Office of Travel Modeling attempted to interpret the location, magnitude, and timing of employment and population growth from master plans while working within the constraints set by municipality or district and year in the adopted forecast.

Socioeconomic and Land Use Analytics Committee

An important element to all DVRPC population and employment forecasts has been consultation and collaboration with county staff with local knowledge of development plans. The Socioeconomic and Land Use Analytics Committee (SLUAC) was formed at the outset of the 2050 forecast process to promote regional dialogue between DVRPC staff and all planning partners throughout forecast development.

The SLUAC is a group of county staff persons from across the region (staff from member cities were invited to participate in 2022). SLUAC membership is generally comprised of those tasked with studies and analysis of demographic, economic, and development data. The SLUAC is set up for collaborative regional data efforts involving members and DVRPC staff. It also fosters regional exchanges of input and ideas, along with identifying best practices when performing various types of analysis.

For the forecast process, SLUAC members were invaluable in reviewing base year data, gathering and commenting on input data for the land use model, and performing reality checks on model results. They gave insights into current and expected trends for their individual counties and the growth to expect within them. SLUAC members passed on their local knowledge and experience when reviewing datasets. For example, when tasked with reviewing the point-level employment data from the National Establishment Time-Series (NETS) that has been used in past forecasts for base level employment, experienced county staff shared lessons learned on how to make that data review most effective.

Land Use Modeling for Concurrent Small and Large Area Socioeconomic Forecasting

DVRPC procured a subscription to UrbanSim, LLC's web-based model platform, UrbanCanvas, in early 2019 and began a contract for land use model development. UrbanSim is the most widely used land use model among larger metropolitan planning organizations (MPOs) across the country. Land use models like UrbanSim are designed to allocate development, households, and employment to small geographies within a region with outcomes based on factors like costs, accessibility, and observed behaviors of actors such as developers, households, and businesses.

UrbanSim replicates locational choices of households and employment concurrently, understanding that the location of employment of various types will be relevant to the location and accessibility required for certain households, and conversely, accessibility of workforce and customers will influence business locations.

DVRPC's UrbanSim model used for the 2015–2050 forecasts allocated change by 2010 census block geographies. With a base geography of census blocks, modeled outcomes can be aggregated to multiple higher geographies, such as block group or tract. Block geographies also nest within county and municipal or district geographies at which the forecast is adopted.

Travel demand model zones are also composed of census blocks and nest within municipal and district boundaries. The UrbanSim model outputs multiple variables required for travel model zonal inputs. At every geography, UrbanSim outputs population cohorts, household types, and employment sectors that the travel model requires to estimate travel demand in the region.

With forecasts developed and reviewed by the SLUAC at a small area level—prior to adoption—studies and analyses using UrbanSim forecast results as inputs to the travel demand model receive a level of scrutiny from county staff on the assumptions feeding the travel model that had not been previously incorporated into the process. This reduces staff and partners' efforts at the outset of studies to review and approvals of small area conditions and growth assumptions. The UrbanSim model also simulates socioeconomic and land use results for each year, not just every five. This is useful, as some travel model projects and studies require base and future years that do not end in zero or five.

Some of the intricacies of the DVRPC UrbanSim model developed for the latest forecast and how it was integrated into the forecasting process are described in the following sections on process and methods. Also highlighted are known limitations of the model or how it was initially implemented, given constraints on development time or the model's functionalities available when forecasting.

Base Year Creation

Population Base

Forecast years skip by five-year increments. Base years too will end in zero or five. The preferred source for base year population would be the most recent decennial census count. However, this forecast needed to be adopted in the months preceding the first 2020 Census release. When more than five years have transpired since a decennial count the base population comes from municipal estimates of population from the U.S. Census Bureau's Population Estimates Program (PEP). PEP releases provide annual estimates for population based on administrative records of births, deaths, and domestic and international migration and is the most authoritative value for population in intercensal years. PEP data is released each year, with an estimate for the population for July 1 of the prior year, as well as corrections for July 1 of each prior year, back to the year of the last decennial count.

The PEP release used for base year population in this forecast was the 2019 PEP dataset. Since the smallest geography for PEP data is municipality, the 2015 Philadelphia PEP estimate was allocated to its 18 planning districts using an assignment of tracts to district geographies and applying the district sum's share of the county sum in the 2013–2017 American Community Survey (ACS) to the PEP total.

A base year migration plan was implemented by the UrbanSim team, in consultation with DVRPC staff, to transition the model from its native base year, 2010, to 2015 by adding residential units built between 2010 and 2015 and filling them at the block level with households sampled from the 2013–2017 ACS Public Use Microdata Sample (PUMS) release allocated to the attributes of 2013–2017 ACS block group households. This data was post-processed to fit the municipal- and district-level values from the 2015 PEP data.

Employment Base

The NETS employment data, produced by Walls & Associates, was used for the third time in a DVRPC forecast for base year employment. The NETS database is essentially a "cleaned-up" version of the Dun & Bradstreet database containing point-level locations of employers. Using each company's unique DUNS number (or numbers, in cases where separate divisions within a company have unique DUNS numbers), Walls & Associates creates a time series for each business and then screens the data to eliminate duplicates and identify anomalies. If a file contains suspicious information, the data is cross-checked with previous annual records and adjusted or eliminated as appropriate, based on information collected from other sources (including government and nonprofits). One advantage of the establishment-based NETS Database is that all employment, sales, and other activity is reported at the actual facility—not the headquarters.

Unlike many government sources of employment data, the NETS database includes sole proprietors, part-time employment, and farm operations, and has been found to be more accurate in reporting data for small privately-owned firms and public sector employers such as post offices and public schools. Employment from the NETS database is therefore generally higher than many of these other sources.

In December 2018, DVRPC acquired an updated NETS dataset with 2015 employment data. All corrections made to the previous NETS database by DVRPC and county planning staffs, either during the previous forecasting round or as a result of ongoing DVRPC land use and transportation studies, were incorporated in to the new database. DVRPC staff reviewed the revised 2015 data reducing duplicates and correcting obvious errors, using resources that included CoStar, company websites, and online business directories. The data was then reviewed by SLUAC members, and further corrections were made based on local knowledge (including errors in location and missing large employers).

The NETS database used by DVRPC includes the street address and the most current latitude-longitude for each establishment as well as the origin and destination latitude-longitudes for all significant moves, at the four-decimal-place-level. In order to assign each employer to a specific municipality, every employer in the NETS database was geocoded. Based on an internal review by DVRPC staff, several spatially inaccurate results were identified, and numerous adjustments were made to improve the accuracy of the dataset before the results were sent to the counties for review. A detailed explanation of the quality control/quality assurance procedures for cleaning the 2015 NETS data purchased and other additions to the base year employment data are found in Appendix D.

The native UrbanSim employment data source is Longitudinal Employer-Household Dynamics (LEHD) data but that data was swapped out with block-level sums of NETS data by the two- and three-digit North American Industrial Classification System (NAICS) codes when the model's base year migrated to 2015.

Disaggregate Synthetic Agents

DVRPC's UrbanSim model consists of multiple submodels that attempt to replicate real world conditions and the decision-making process of various actors, or "agents." Individual data records are kept for each "synthetic" household and its synthetic household members. Household and person records are drawn from PUMS data. Similar to the synthetic population and synthetic household tables, PUMS data provides detailed individual records from a small but representative sample of respondents to the ACS within the Public Use Microdata Areas (PUMA) geography.

Demographic Information

Households

From PUMS household records the UrbanSim households table provides data on:

- the number of:
  - people;
  - children;
  - workers;
  - vehicles owned;
- the householder's:
  - age;
  - race;
  - Hispanic origin;
- the annual income of the household;
- information on their dwelling:
  - whether they rent or own;
  - if it's multifamily or single-family; and
  - whether they moved there recently.

Household Population

Tied to each household record, by a household identification number is a table with a record for each member of the PUMS household records. Synthetic population records specify each household member's:

- age;
- sex;
- race;
- Hispanic origin;
- relationship to the householder;
- educational attainment level;
- information on students:
    - student status;
    - grade;
- information on employed person:
    - worker status;
    - hours worked per week;
    - work at home status; and
    - individual annual earnings.

From a process of sampling PUMS records by the large subcounty geographies known as PUMAs, the synthetic households and population were originally assigned with a block ID by a fitting process that tied household agents to smaller geographies within the PUMA by control variables from the 2008–2012 ACS and 2010 Census, based on what metrics were available at the tract, block group, and block levels. This reflected the standard, precalculated model specification included in any 2010 base year UrbanSim purchase. Later, by adding residential units built between 2011 and 2015, and using 2013–2017 ACS data from PUMS and standard tract and block group tables, the demographic data in the model was migrated to a 2015 base year.

Residential Unit Information

Residential units were individually attributed to the block using 2010 Decennial data. As noted above, new residential units added between 2011 and 2015 were added when migrating to the 2015 base year. Attributes of residential unit agents are:

- residential unit ID;
- block ID;
- year built;
- building type:
    - single-family rental;
    - single-family owned;
    - multifamily rental; and
    - multifamily owned

Importantly, there is no attribute that ties residential units to a household record. Vacancy rates are determined at the block level as the sum of all households divided by the sum of all residential units sharing the same block ID.

Employment Information

Employee records are synthetic agents in the model. The native UrbanSim product used the U.S. Census Bureau's 2010 LEHD Origin-Destination Employment Statistics (LODES) data, but the DVRPC model swapped that out with

2015 NETS data purchased by DVRPC and cleaned by DVRPC and SLUAC members. Tied to each employment record is that employee's:

- employee ID;
- block ID;
- industrial sector:
  - three-digit NAICS code
  - two-digit NAICS code; and
  - sectors generalized into six categories.

Unlike, the relationship of persons to households, employees are not tied to a company, and so when employees of a certain sector move to a block, it's akin to a new company or companies of that type moving there, but not structured as such. And different from the concept of households moving to a block if current residential units outnumber households, there's no notion of commercial buildings within a block at all. Discussed in the Supply-Side Restrictions section below, blocks have an employment capacity in lieu of calculating vacant commercial space and zoning capacity.

Additional Block-Level Data

Pricing

For the land use model to understand market demand for housing, rental and home sale values, base year home and rent values collected based on ACS estimates and translated to the block level.

Group Quarters Population

Total population is a sum of household population group quarters (GQ) population. GQ population includes institutional (such as, those living in adult and juvenal correction facilities and nursing homes) and noninstitutionalized individuals (such as, those living in dormitories at universities and military barracks). Only household population behavior is simulated in UrbanSim. GQ population totals at the municipal and district level would suffice for the adopted forecast to create a total population in combination with the household population provided by UrbanSim. However, the travel demand model requires TAZ-level forecasts for noninstitutional GQ population. The VisionEval model, a strategic model that provides travel and environmental results that DVRPC plans to use in the future for scenario planning purposes, requires institutional GQ population by block group and age.

DVRPC staff created a table of 2010 Decennial Census group quarters population at the block level stratified by age, sex, and facility type. Not all that information was available at the block level, so a process of iterative proportional fitting (IPF) the data to control totals and distributions at higher geographies was created to achieve a good fit, consistent with Census totals. The 2010 GQ population table was then adjusted to create a 2015 table. These changes were only made where ACS change in GQ population estimates were statistically significant from earlier estimates. Later, further changes were made for a 2019 GQ table using the same process and getting feedback from City of Philadelphia staff, particularly on changes in population at and closings of correctional facilities run by the city.

The initial plan was to keep the GQ population constant for all forecast years since this effort didn't have a model that can predict change for GQ population and given that these facilities don't tend to fluctuate greatly. However, the COVID-19 pandemic led to large numbers of deaths in the region and around the world, particularly for nursing home and prison populations. UrbanSim lacks a good way to adjust individual household population levels to reflect higher than usual death rates. As a result, GQ population was adjusted to decline in facility types warranting greater reductions until 2022, as a reflection of the pandemic's toll on the region's population. After 2023, GQ population assumes a mirrored rebound back to 2020 levels in 2025.

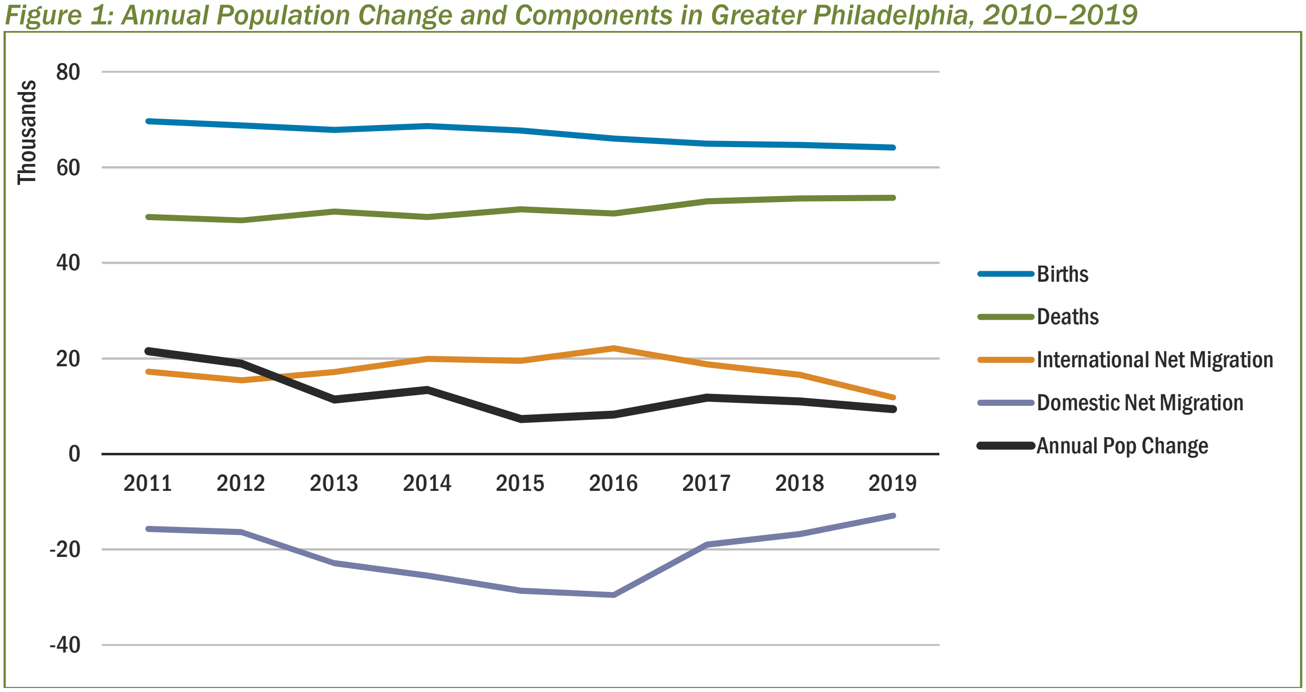
Control Total Development

In order for UrbanSim to allocate new residential units, households, and employment to the region, it needs to know how many households and employees to expect in each simulation year. Some MPOs use macroeconomic models like REMI to develop forecasts for their entire region or individual counties before allocating growth with a land use model like UrbanSim. Some develop a population forecast from an age-cohort model, as DVRPC had done in the past, in order to present counties with one of a couple possible results for population growth.

Trends from available observed data

Before solidifying household and employment control totals for the 2015–2050 population and employment forecasts, SLUAC members were presented with and discussed analysis of observed data trends from recent years. Data from the PEP and the ACS provided insights into the drivers of population change births, deaths, and domestic and international migration. The PEP greatly underestimated regional growth when compared to the 2020 Decennial Census data released after the forecast was adopted. At the time the SLUAC was looking at trends, however, the region's aging population was showing a decrease in births and increase in deaths, such that some counties were already getting more of the latter. Domestic migration was a net negative, regionally, but was showing signs of potentially becoming positive if the direction of change from recent years persisted. International migration had halved itself since a peak prior to the anti-immigration policies of the federal executive branch at the time. Figure 1 shows some of the population trends presented to the SLUAC members at the time.

Figure 1: Annual Population Change and Components in Greater Philadelphia, 2010–2019



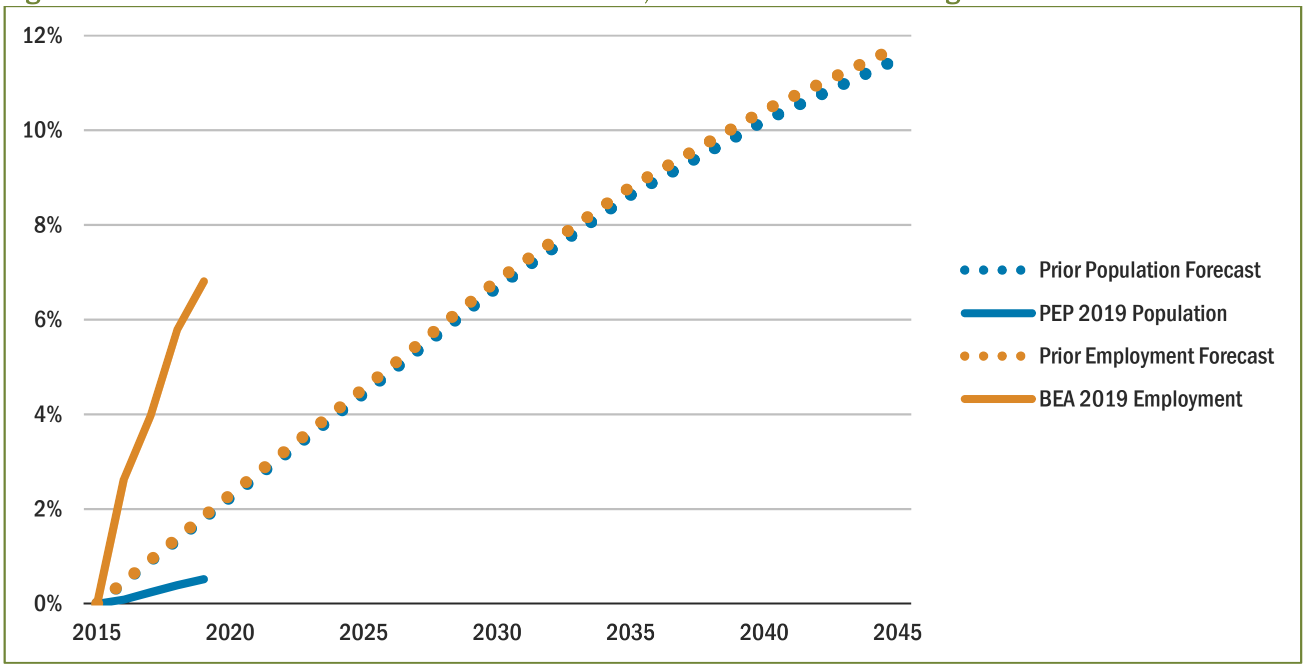
Source: U.S. Census Bureau's Population Estimates Program (2019 vintage)

The pandemic weighed heavily into near-term and potentially long-term forecast considerations in the discussions. Deaths were certain to increase, and births drop more rapidly in the early 2020s from data released by the CDC and observations of experts. It was unclear when those COVID impacts might wane. Similarly, on the international migration front, borders were largely closed, though a rebound of immigration was expected when pandemic concerns subsided, especially when it became certain there would be a change in administrations.

Employment sources like the Bureau of Labor Statistics (BLS) and the Bureau of Economic Analysis (BEA) showed a very different story than the population statistics. The 2010s had seen a decade-long boom in employment coming out of the great recession, with record low unemployment rates. Figure 2 shows just how divergent the available observed data trends were from 2015 to 2019, relative to the prior DVRPC forecasts, which saw population and employment as closely tied through the forecast period.

In the midst of the pandemic, it was clear that 2020 employment would end well below where it started that January. Particular sectors were hit the hardest, such as Food and Accommodations, while some, like Transportation and Warehousing, were suspected to see greater gains due to increased reliance on ecommerce.

Figure 2: Prior Forecasts and Available Data Trends, Cummulative Percentage Growth rom 2015



Source: DVRPC, 2016; PEP 2019, BEA 2019

Developing county targets

DVRPC purchased a detailed macroeconomic forecast from IHS Markit's proprietary models. The IHS Markit forecast gave annual historic and forecasted data on population by age, households, by age of head, and employment by two-digit NAICS code, as well as other metrics. The forecast purchased was from October of 2018, so, while it did provide optimistic and pessimistic estimates, along with a baseline forecast, it was created before the COVID-19 pandemic was at all on anyone's radar. Even its pessimistic results couldn't speak to the rapid change and potential recovery outcomes of the socioeconomic conditions of the time. IHS Markit forecasts were shared with the SLUAC members, and were generally for the region much lower than DVRPC's 2045 population projections and slightly higher than the 2045 employment projection.

Similar to prior forecasts, DVRPC staff felt it was best to send the counties more than one county-level possibility to consider and then provide feedback. Counties received trend line graphs and data tables for both county population and employment consisting of four decades of historic trends, an estimated pre-COVID 2020 and six scenarios out to 2050 from there:

- No recession with
    - The prior DVRPC forecast's growth rates
    - IHS Markit growth rates
- A recession simulation where employment didn't rebound to 2019 levels until 2025 and population trends slowed followed by
    - 2020–2045 growth rates applied from 2025 out to 2050 from
        - The prior DVRPC forecast
        - IHS Markit forecast
    - 2025–2050 growth rates applied from 2025 out to 2050 from
        - The prior DVRPC forecast (2046–2050 extrapolated)
        - IHS Markit forecast

The counties were presented with these figures. They then provided DVRPC with a target 2050 population and employment value they thought would be reasonable to be in the ballpark of, as well as some narrative on their outlook for county growth. They also provided interim growth targets of what they might expect in five-year increments.

Household Control Totals

DVRPC staff subtracted group quarters population from counties' total population targets to get household population targets for each five-year period. Those were then converted to household counts using mean household size factors. Population to household ratios were refined by testing how UrbanSim household controls translated to household population results. Intervening years were calculated to transition smoothly to each five-year increment. PEP estimates for 2015 to 2019 were used to create a forecast adhering to recent population change.

Ideally, UrbanSim should use region-wide controls and allocates to the block level in such a way that the sum of blocks by county hit close to observed or forecast county totals; however, if regional controls diverge from targets, subregional controls can be used to force the model to fit certain criteria. For the population forecast, training the model to hit targets was more difficult without prescribing some subregional outcomes. Control totals were divided into 3 geographies:

1. Philadelphia
2. the sum of the four remaining southeast Pennsylvania counties
3. the sum of the four New Jersey counties

Household control totals don't need to be purely totals of households per year. New households added could be by any single household attribute, like household size segments (1-person, 2-person, 3-person, 4- or more persons) or combined attributes (low income, 0 workers; low income, 1 or more workers; high income, 0 workers; high income, 1 or more workers). To try to forecast a known aging population, staff attempted to segment household controls by age of the household head (using IHS Markit forecast distributions), with older household heads gaining in proportion to younger ones over time. Prior to the forecast, initial results of these segmented household types were yielding disproportionately slower growth in some counties. Having limited time to investigate the cause, household totals were ultimately used. Further experimentation with segmentation of control totals is recommended for future UrbanSim use, as this can be a key tool in setting the direction of overall regional trends. Household control totals can be found in Appendix C.

Employment Control Totals

Employment controls were used regionally, and segmented by two-digit NAICS codes. All Manufacturing is typically a group of all codes beginning with 31 through 33. However, for the forecast, each of these codes31, 32, and 33—were treated individually to better account for distinctions in nondurable goods (codes starting with 31 and most of those starting with 32) and durable (codes starting with 33). These sectors have been moving in different directions with nondurable increasing in the region, while durable has been declining. This was important, as three-digit codes by TAZ were later exported from UrbanSim for use in the freight model DVRPC's travel model team was developing. Similarly, Public Administration (92), State and Local Government and Federal Government were individually treated. Armed forces were separately forecasted as well.

The source of early year employment sector controls were applications of growth rates from observed BEA data to the 2015 NETS sector sums for 2016–2019, fitted to total growth rates applied to NETS totals. 2020 employment used an early BLS release of monthly sectoral totals by Metropolitan Division geographies for January to December for 2020. The last three months' data were marked as preliminary. Averaging these monthly totals and comparing them to the monthly averages of 2019 created annual change rates by sector reflecting some semblance of the impact the pandemic had had on employment throughout the first year of the pandemic. For counties without individual reports, the parent Division's sector change rates were applied then fitted to total employment change rates. Since employment control totals were regional, the declines in various sectors would have been treated with uniform declines in each block across the region. There is no employment loss submodel within UrbanSim that predicts the locations that are hit by regional declines more than others. To accommodate the county-level differentiation of impact to sectors in 2020, the UrbanSim team created an external procedure to run with the 2020 simulation that would uniformly decrease employment of any declining sector within that geography, rather than regionally.

The 2021 to 2050 totals were developed first from a conservative assumption of recovery in total employment exceeding the prior 2019 peak by 2025, then adhering to summed county growth targets for 2030 to 2050. The sectoral distribution was first an application of IHS Markit forecast growth rates by industry, but then adjusted to consider trajectories of sectors seen in BEA employment trends, as well as assumptions on potential pace of recovery out of the pandemic for particular industries. This made some industries exceed their 2019 peaks more quickly than 2025 and some never quite reach them, especially if they were on a downward trend pre-Covid. The initial pass at creating employment controls by sector was sent internally to relevant DVRPC staff. After applying some staff suggestions, the controls were finalized. These can be found in Appendix C.

Individual Behavior and Simulated Conditions

UrbanSim contains individual records of residential units, households, and employment, allowing these agents to make decisions on where they want to locate based on probabilities. Triggered by a simulation year's control total increases, submodels within UrbanSim calculate these probabilities and place newly added household and employment records within blocks.

UrbanSim Submodels

Location Choice Models

To maintain an assumed regional vacancy rate, new residential units are created and allocated based on considerations a real estate developer might use for site selection. UrbanSim's submodels listed below are designed to make probable location choices for each new record:

- Residential Development Project Location Choice Model (RDPLCM)
- Household Location Choice Model (HLCM)
- Employment Location Choice Model (ELCM)

Location choices are based on the record's attributes and it's the conditions at potential block locations in the region. HLCM and ELCM allocate new households and employment for each simulation year's control total increases. The RDPLCM allocates new residential units based on the addition of households and a regional vacancy rate. For the 2015–2050 forecasts a vacancy rate from the base year, 6.7 percent, was used. Adding households without the addition of new residential units would create a lower vacancy rate. The RDPLCM builds enough residential units to reach the regional vacancy rate and then stops "building."

At the time of the forecast, DVRPC's UrbanSim model could not apply a different vacancy rate for each subregion's household control totals. Since the suburban Pennsylvania counties had a lower actual vacancy rate than the regional average and Philadelphia's vacancy rate was higher, this temporarily inflated residential unit production in the Suburban PA counties for the 2020 simulation year, while keeping the Philadelphia housing increase tied only to the programmed units in the development project pipeline data explained later in this report. New Jersey counties' vacancy rate was relatively on par with the regional rate. After the forecast, the DVRPC UrbanSim model was improved with the ability to assign a vacancy rate for each subregion used in control totals.

Pricing Model

The location choice models base some probabilities on block-level market values for home purchasing and rental units. The Real Estate Pricing Model (REPM) simulates changes to averages sales and rental prices in each block so that the location choice models can respond to market conditions.

Relocation models

UrbanSim allows for location choices of not just new agents added to the region via control total increases, but also those of current synthetic "residents" who choose to move within the region. The relocation models use probabilities for relocation by segment type or just total relocation rates to identify relocating agents, and then add households and employees to the HLCM and ELCM, respectively.

Household and employment relocation models were employed for years 2015 to 2019. Without them, municipalities with known declines in population were unable to reflect those realities and not enough agents were added in control total increases to be able to fill newly built vacant residential units. The 2019 forecast results were postprocessed to better fit the PEP totals and sectoral employment totals. These are further explained in the two-phased forecast section later in this ADR. There was not adequate time to develop and test the relocation model prior to the 2050 forecast. As a result, relocation models were disabled for 2020 to 2050 in order to better understand their results before applying them to future year forecasts.

Submodel Segmentation

In each simulation year, the UrbanSim location choice submodels group new residential units, new households, and new employment—determined by vacancy rate assumptions, household control totals, and employment control totals—into groupings or "segments." Each new record falls into a segment that determines its probability of where to locate based on local conditions. The same happens with the pricing model. Local conditions determine whether sales or rental values increase or decrease.

The groupings or segments of the submodels are as follows:

Residential Development Project Location Choice Model

The two RDPLCM segments are unit types:

1. single-family; and
2. multifamily.

Household Location Choice Model

The eight HLCM segments are combinations of tenure status, household size, and age of householder, as seen in Table 1.

Table 1: Household Location Choice Model Segmentation

		Segments							
Demographic Attributes		1	2	3	4	5	6	7	8
Tenure Status	Owned	●	●	●	●				
	Rented					●	●	●	●
Household Size	1 Person	●	●			●	●		
	2+ Person			●	●			●	●
Householder Age	Under 55	●		●		●		●	
	55+		●		●		●		●

Source: DVRPC, 2021

Employment Location Choice Model

Seen by their component two-digit NAICS code level in Table 2, the segments of the ELCM can generally be described as:

1. Management, Public Administration
2. Basic Industries
3. Transportation, Communications & Public Utilities, Warehousing
4. Retail Trade, Accommodations, and Food Services
5. Finance, Insurance, and Real Estate
6. Services

Table 2: Employment Location Choice Model Segmentation

		Segments					
Two-Digit NAICS Sectors		1	2	3	4	5	6
11	Agriculture, Forestry, Fishing and Hunting		●				
21	Mining, Quarrying, and Oil and Gas Extraction		●				
22	Utilities		●				
23	Construction		●				
31–33	Manufacturing		●				
42	Wholesale Trade			●			
44–45	Retail Trade				●		
48–49	Transportation and Warehousing			●			
51	Information						●
52	Finance and Insurance					●	
53	Real Estate and Rental and Leasing					●	
54	Professional, Scientific, and Technical Services						●
55	Management of Companies and Enterprises	●					
56	Administrative and Support and Waste Management and Remediation Services						●
61	Educational Services						●
62	Health Care and Social Assistance						●
71	Arts, Entertainment, and Recreation						●
72	Accommodation and Food Services				●		
81	Other Services (except Public Administration)						●
92	Public Administration	●					
n/a	Armed Forces	●					

Source: DVRPC, 2021

Real Estate Pricing Model

The REPM is simply segmented into residential units':

- Average sales price; and
- Average rent.

Explanatory Variables

UrbanSim has a variety of location choice and other submodels. Each submodel is divided into segments, composed of similar individual agents. Each segment has a set of characteristics that are important to its agents weighing locations decisions. These sets of characteristics are called "explanatory variables" because they explain the factors agents weigh as they make location choices. Explanatory variables make agents responsive to the characteristics of a block and the surrounding blocks accessible to it.

In a process called model estimation, base year location of each segment is tested against various potential explanatory variables with a regression analysis to determine to which factors the segment is most responsive. Statistically significant variables become the explanatory variables. The segment's coefficient values for each explanatory variable, in combination with each other, are used when an agent from a segment evaluates location options. The variables are assigned a negative or positive coefficient value that determines the probability of locating in each census block. Negative coefficients will work to deter the choice of a location, and positive will make it more attractive. The larger the absolute value of the coefficient (i.e., the further away it is from zero in either direction), the stronger its influence on location choice will be.

Model segmentation and explanatory variables selection are important to designing a model that's sensitive to particular variables users wish to forecast and analyze. For instance, without segments or explanatory variables that deal with income levels of households, it's difficult to claim that future household income results are potentially valid at small geographies. Further information on explanatory variables, including a list of the more than 45 variables used, is found in Appendix C on model development and configuration.

Survey of Developers and Planners

To inform DVRPC's collection of potential data sources for explanatory variables in UrbanSim, staff developed a survey aimed at developers and planners dealing with development proposals in the region. Professionals dealing with residential and commercial development weighed in on three different areas that may factor into location decisions:

- Policies, incentives, other costs;
- Site's physical characteristics; and
- Site's proximity and access.

From the survey results (summary available in Appendix E), DVRPC staff prioritized the collection of data needed for model estimation, beyond the conditions already present in the UrbanSim model. The survey's findings will continue to be used to guide further data collection in model development efforts.

Interdependence of Submodels and Travel Model Integration

Generally, explanatory variables make their submodel segments responsive to conditions and changes in them from year to year in the simulation. Nearly all explanatory variables are dynamic, meaning densities and proportions of variables change as residential units, households, and employment shift and cause blocks to become more or less attractive to submodel segment than the prior simulation year. Part of the advantage to forecasting population and employment simultaneously within the same model is that changes in employment locations impact location choices for residential development, and demographics and housing characteristics influence employment location choices. Some examples of the kinds of relationships seen in the submodels' coefficients are:

- Multi-person households with a head age 55 or above who own their homes tend to avoid municipalities with higher proportions of retail employment; and
- Each segment of employment will be more likely to locate to a block with more recent residential unit development.

Accessibility to other areas and attributes of the region plays heavily in all explanatory variables of submodel segments, whether rental or home prices, or location choices of residential developers, households, or employment. Accessibility and travel time to amenities in the region are calculated with “skim” matrices from the travel model. For various submodel segments, these matrices of zone-to-zone travel time or distance in the 6:00 am to 10:00 am travel period are used to calculate:

- How many employees or households can be reached in 15 to 30 minutes by any means or by transit (REPM, REPLCM, HLCM, ELCM);
- The distance to key travel facilities like 30th Street Station (RDPLCM);
- The travel time to tier one or tier two universities (REPM, HLCM, ELCM); and
- The travel time to freeway interchanges (RDPLCM, HLCM, ELCM).

UrbanSim can iteratively pass forecasted zonal socioeconomic data of a simulation year to the travel demand model. The travel demand model can then be run for that year, and the resulting skim matrix reflecting new travel conditions can be uploaded into UrbanSim. The travel conditions reflect changes due to new travel demand from housing or employment, or new facilities planned for completion by that simulation year. If a new facility improves travel times, segments responsive to improved accessibility will find blocks closer to the travel network improvement more attractive for location choice.

The pricing model will raise home ownership and rental costs in blocks that increase employment accessible within 15 to 30 minutes due to transportation improvements. An increase in housing costs may make the location unaffordable to some segments of the household location choice model. In this way, the various submodels of UrbanSim and the travel model are interwoven into causal relationships.

Environmental conditions

There is only one explanatory variable that is not dynamic, meaning the value is constant through all analysis years. That is, the percentage of a block’s developable area within a 100-year floodplain. Developable area is determined by the portion of land use types that wouldn’t typically be redeveloped and protected open space polygons do not overlap within each block (see Appendix C for more detail on developable land definitions). Recent improvements to the UrbanSim model will allow it to expand or contract floodplain areas in each block in future years in order to simulate potential for climate change scenarios where flooding deters location choice. The floodplain variable was only statistically significant to the pricing model’s rental prices and all segments of the ELCM.

Calibrated coefficients

UrbanSim model can be run with calibrated or uncalibrated coefficients. In a calibrated model run, the magnitude of the explanatory variables’ impact on probabilities are adjusted so that the model hits targets based on observed change within the region over time. DVRPC staff collected data on county and municipal/district-level change in a three- to eight-year period. The following sources were used to set change targets:

- Household population;
    - County: PEP [2019 vintage], 2011 to 2019 change;
    - Municipal/district: PEP [2019 vintage], 2011 to 2019 with ACS-based district sums used to apply the proportion of Philadelphia Planning Districts’ populations to the city-wide PEP estimates;
- Residential units;
    - County: PEP [2019 vintage], 2011 to 2019 change;

- Employment;
    - County: BEA, [Nov. 2020 release] 2011 to 2019 change by six segments in ELCM; and
    - Municipal/district: LODES [V7.4], 2015 to 2018 change by six segments in ELCM.

The calibration occurs on multiple geographic levels and year ranges, and is aided by a statistical method called auto-differentiation. With the adjusted coefficients, the behavior of location choice models' agents can be informed by the relationships identified in model estimation and perform similarly to recent growth patterns. Calibrated coefficients were employed for the simulation results from 2015 to 2019, as that period was largely reflected in the calibration targets.

Uncalibrated coefficients are simply the coefficient results from model estimation, prior to calibration adjustments. Due to the uncertainty as to whether the same kinds of growth would occur in future decades as did in the prior decade—especially in light of the Covid-19 pandemic and its after-effects, the 2020–2050 simulations were left uncalibrated. Uncalibrated coefficients were also found to better fit county and municipal targets for 2050.

Supply-Side Restrictions

UrbanSim simulates real world demand for residential unit and employment location choice through agents' explanatory variable coefficients; however, a key real world factor is the limited supply of residential units, development capacity (either new developable land or the ability to increase density in existing developed areas), and employment space. UrbanSim attempts to replicate this reality in two ways:

1. Households can't exceed the number of residential units available in a block. Even if a block is attractive for the HLCM to send agents to, it won't be able to unless there are vacant residential units available. However, there is no assignment of a household to a particular unit.
2. Each block has "constraints"—a proxy for zoning—which can be adjusted for future years for scenarios of anticipated up-zoning or down-zoning.
    - A max capacity for residential units; and
    - A max capacity for employment.

Figure 3 gives a graphic representation of these concepts in an example block. The example block spatially resembles one with single use areas of residential and non-residential, each of these sections have an area that is built out and another with greenfields zoned for further growth. However, this is just one possible scenario for a block's spatial arrangements. Mostly, it serves to demonstrate the concept that a block may contain:

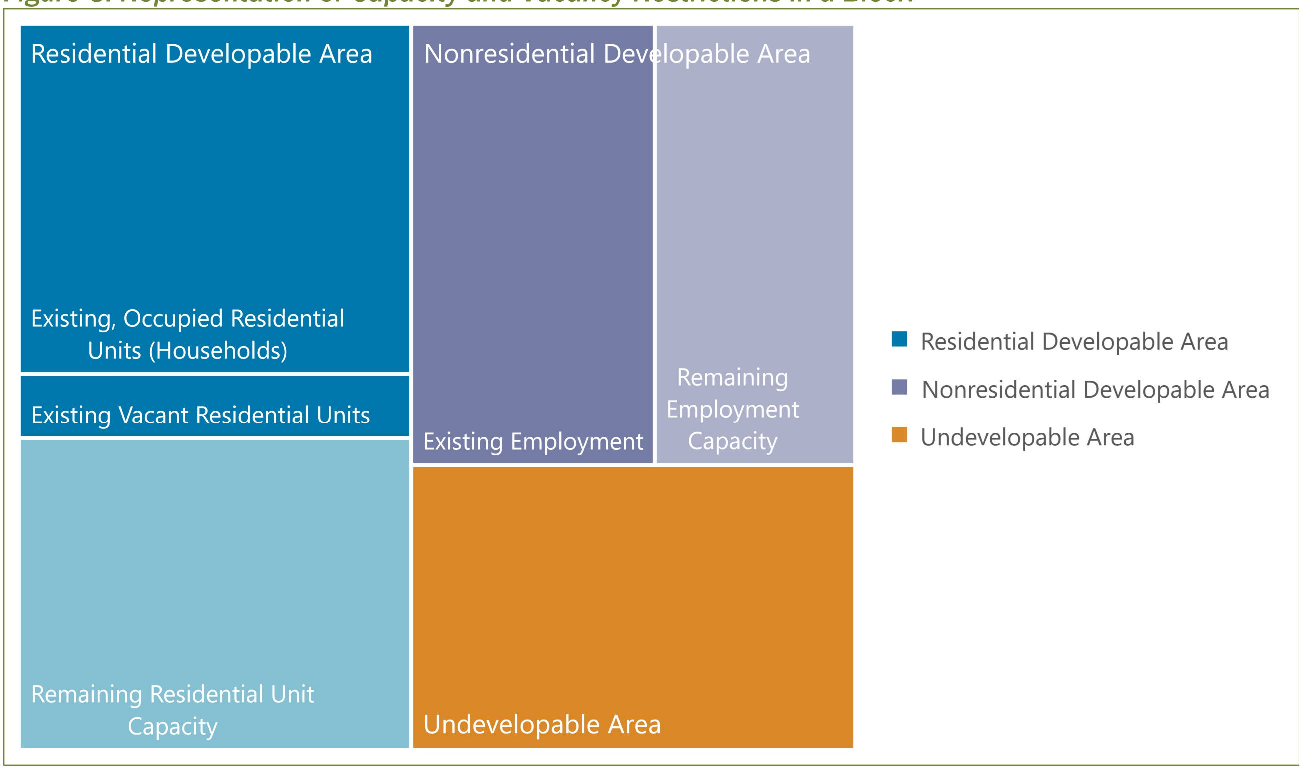
- Total block area = developable + undevelopable space;
- Residential unit capacity within the developable area = existing residential units + remaining residential unit capacity;
- Existing residential units = vacant residential units + occupied residential units (otherwise known as households); and
- Nonresidential employment capacity within the developable area = existing employment + remaining employment capacity.

UrbanSim allows for mixed use within a block, it's just agnostic on whether or specifically where the mix of uses is occurring within the block. It is also agnostic as to whether the remaining capacity is found in developable greenfields or whether through higher densities resulting from infill projects built among existing development.

Unlike Figure 3, the model only knows each block's total capacity for residential units and total capacity for employment. It prohibits residential units from exceeding residential unit capacity and employment to exceed employment capacity. Within the block, residential units and employment may be mixed use—meaning both uses are located within the same buildings—or single uses that exist in entirely separate areas. Existing development may cover the whole block and capacity may only allow for infill or it could consist of greenfields, or a mix of both. None of these variations change the calculation of what's existing and what capacity remains.

Mirroring the real world, existing residential space is quantified by total residential units. While the households in the block are not assigned to residential units, the household count can't exceed total residential units. Diverging from reality, non-residential space is not tracked in UrbanSim, so a maximum existing space within which employment can fit does not exist either. New employment can locate within a block when known new nonresidential space appears in the programmed development pipeline (discussed below). To facilitate this, the model adds "built" employment capacity to the block when a new "nonresidential building" is completed.

Figure 3: Representation of Capacity and Vacancy Restrictions in a Block



Source: DVRPC, 2022

Creating a Proxy Zoning Layer

Constraints were calculated using the zoning code boundaries from nearly all the region's municipalities. DVRPC staff went through an effort to find recent geographic information system (GIS)-based zoning shapes covering eight of nine counties fully. About half of Camden County's municipalities had GIS files reflective of their code. For the remainder of the county, shapes of the major categories in the DVRPC 2015 Land Use Inventory were used as a proxy for what was allowable.

It was unrealistic to collect the actual zoning codes and overlay considerations for all 350 municipalities in the region. Philadelphia's zoning code was analyzed to develop capacities that are reflective of its residential unit and gross floor area maximums because it covers a large area of the region and it's a location where a lot of development occurs.

Zoning is parcel-based; however, constraints are block-based. Blocks may have multiple zone types within them. It is only necessary for the blocks to reflect the aggregate of what may be allowable within them, not the precise location of new development.

The first draft block-based constraints were created by using the densities of residential units from the 2010 Census within each municipality's residential zones. Each zone type would have a wide range of what had been made allowable based on observed data in 2010. For example, small blocks reflecting street rights-of-way can sometimes erroneously get assigned residential units when mapped from street addresses. This and other potential data flaws can create very high densities in blocks. To avoid these outliers, the 80^{th} percentile of densities within a given zone was used. Similarly, the 80^{th} percentile of 2015 NETS densities within a municipality's various commercial zones were used to determine the max allowable density of employment.

Adhering to a precise allowable residential units or employment maximums that might be allowable with commercial square footage was not the goal in the constraints developed for UrbanSim. Since the forecast has a goal of approximating a plausible future outcome, the capacities of blocks in the model constraints were designed to reflect the fact that zoning codes are not always the determining factor on what or how much gets built. For example:

- zoning can be overwritten with code changes, variances, and other exceptions for development projects;
- developers, elected officials and/or communities can seek changes or exceptions if they want something built that diverges from the code; and
- some "anti-growth" communities create an environment where certain locations are not likely to approach the maximums allowed on paper.

The initial draft constraints were adjusted to be reflective of the probability of growth in the face of demand due to the malleability of zoning codes and the imprecision of the 80^{th} percentile approach. Early 2020 to 2050 simulations were tested for ability of draft constraints to produce growth rates that were somewhat in line with prior municipal forecasts. When a municipality or district received population or employment growth well beyond what prior DVRPC forecasts had foreseen, capacities were constrained to reach a more plausible outcome. Later, county review of draft results created further opportunity to discuss what reasonable growth in places with high demand might look like. SLUAC members conveyed comments on municipal results indicating certain places were already fairly built out and that results were too high where the model saw demand but didn't know the limits of what build-out would be.

Real Estate Development Pipeline

In addition to the introduction of a behavioral model making probabilistic choices on where employment, residential units, and households will locate, the 2050 population and employment forecast was bolstered by data on near- and long-term planned real estate development projects. This first-time regional dataset was developed by DVRPC staff in collaboration with county partners. Proposed and under construction from CoStar's commercial and multifamily database was a key starting point in the effort. Newspaper articles and social media announcements of projects augmented the list.

DVRPC and County staff worked together to gather additional sources of information. There were efforts to interpret the scale and phasing of transformative master plans, often the source of the most distant completion years in the pipeline. Since data was collected in 2020 and into 2021, recent development with completion years of 2016 to 2020 were used as "future" development from the 2015 base year. Recently built single-family residential unit

A hallmark of the DVRPC forecasting process has always been its engagement with county partners to ensure local knowledge and ground-truthing. UrbanSim has enhanced collaboration with partners by allowing them to see inputs and outputs of the model displayed on the map. SLUAC members were given login credentials to the web-based UrbanCanvas Viewer platform where they could see mapped layers posted for their review, and they could mark locations with comments on missing pipeline projects or unexpected results for DVRPC staff to respond to in the next draft simulation until they had a model results they were comfortable with.

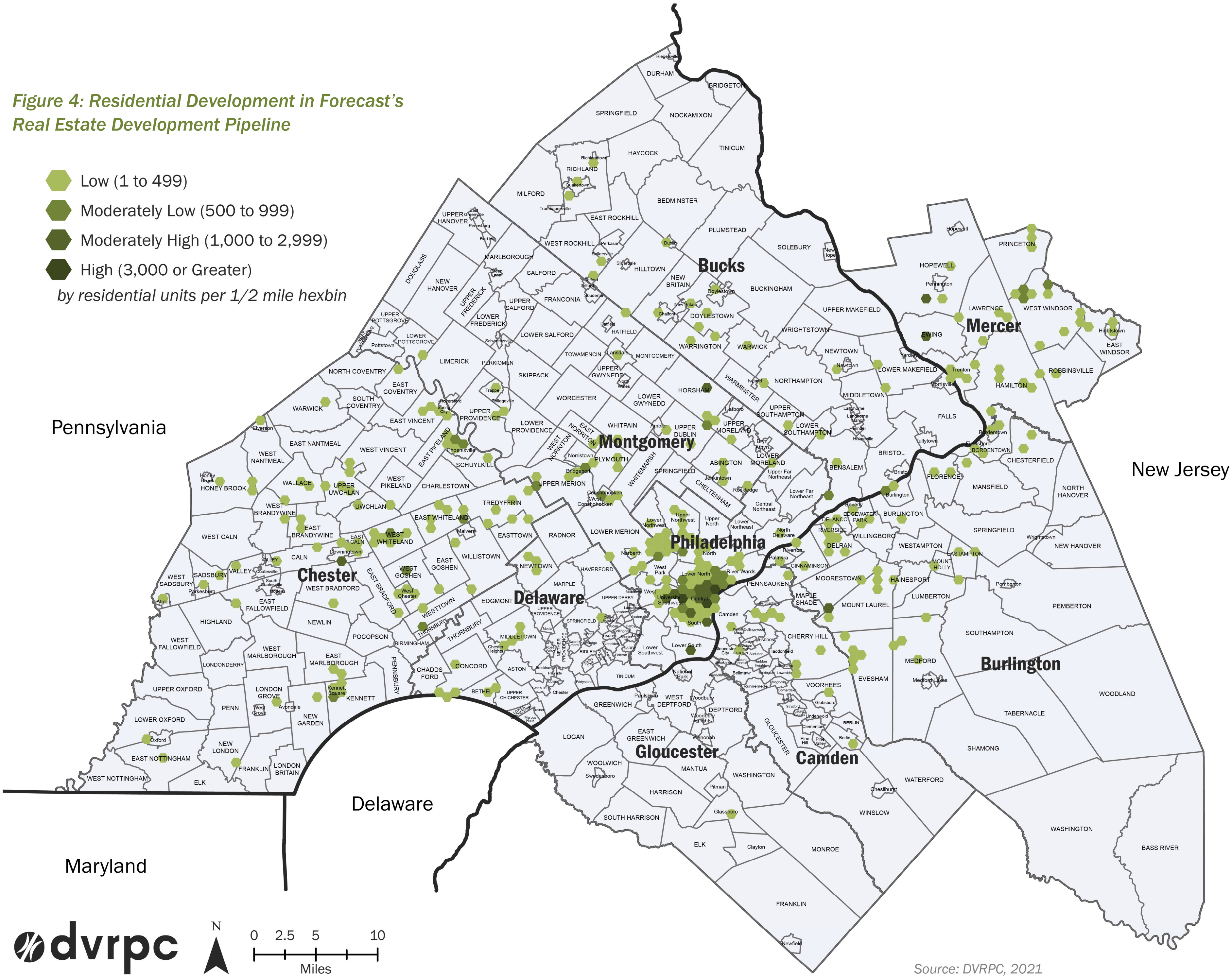
data was derived from parcel files and assessor data from each county. Counties with GIS resources of subdivision plan approvals and other developments worked with DVRPC staff to identify upcoming projects missing from the draft pipeline. DVRPC has a NearMap subscription that gives access to detailed aerial photography of the region with three sets of images taken each year. This aided the determination of the project status and helped pinpoint the completion year. Perceived stage of construction informed assignment of near-term completion years for projects underway. For projects yet to break ground, completion year assumptions were applied relative to plan approval year.

Figures 4 and 5 display regional concentrations of development pipeline projects used in the population and employment forecasts. Figure 4 shows the residential project concentrations by number of residential units and Figure 5 shows nonresidential square footage added. Both figures make use of hexbins, which are hexagonal polygons—in this case, a half-mile wide—summarizing all residential units or nonresidential square footage within them.

DVRPC's UrbanSim model largely works at the census block level, as stated, however, it was designed with an interconnected parcel-level platform. After compiling a regional parcel layer within the model, pipeline projects' locations were assigned to parcels throughout the region. Each project in the pipeline used in the 2015–2050 forecasts was tagged as such to catalog forecast assumptions. In future studies, the final forecast scenario can be reproduced with new real estate projects added or those that appear no longer viable removed.

Each parcel is associated with its census block ID so that new projects can be summed by block, development type, and simulation year. With this information, block vacancy levels increase with the addition of newly built residential units, and employment capacity derived from square footage of newly built nonresidential buildings is added to each block. When household control totals increase for a simulation year, newly added vacant residential units from pipeline projects are prioritized for filling first, before the model allocates the remaining households using the HLCM. Similarly, new commercial square footage in the pipeline translated to added block employment capacity with a per square foot employment factor. New employment added to the region is prioritized for allocation to these blocks with increased capacity to replicate "filling" the new commercial space. Then the ELCM allocates the balance of employment added for that year in the most attractive blocks where employment capacity remains.

Figure 4: Residential Development in Forecast's Real Estate Development Pipeline



Source: DVRPC, 2021

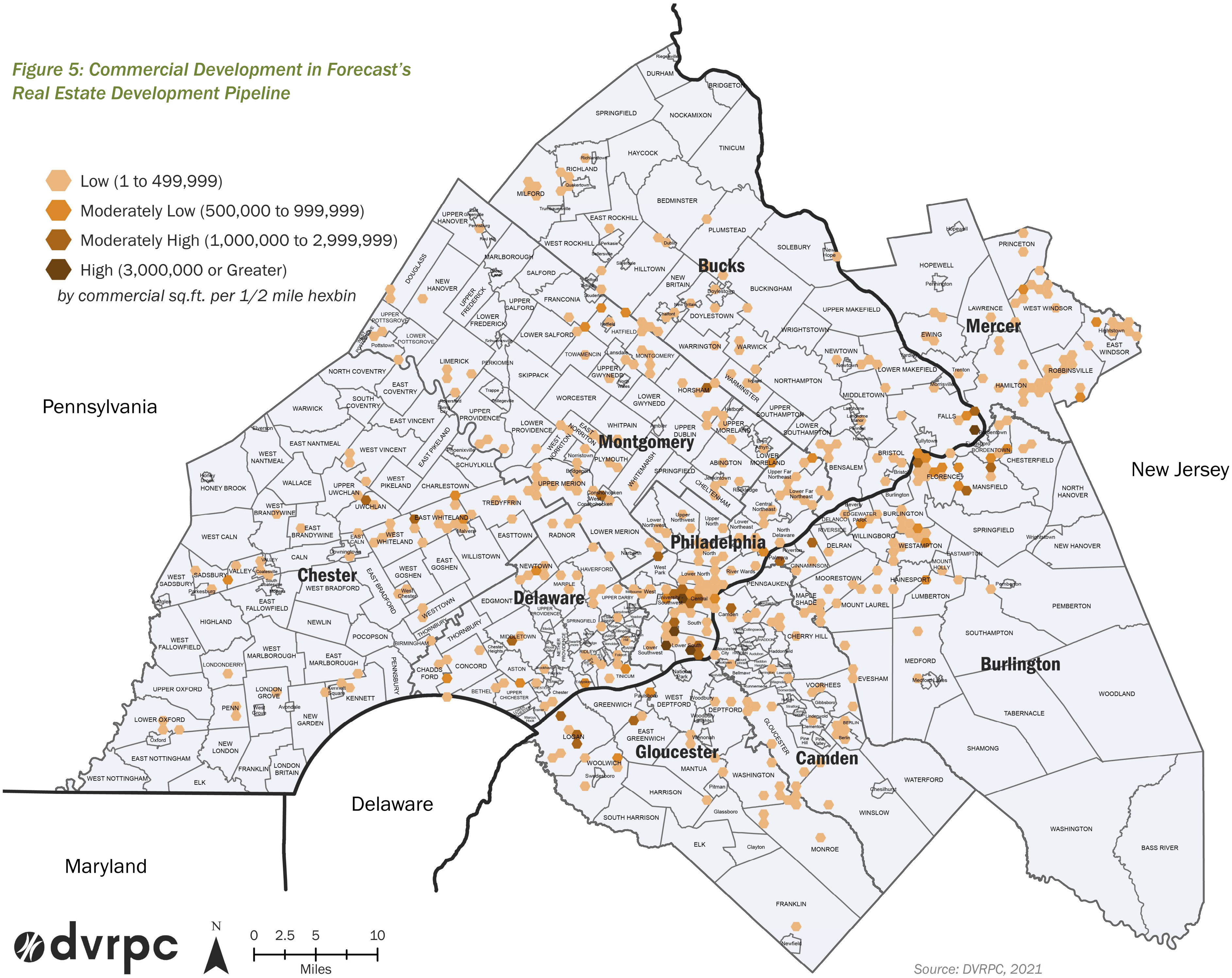
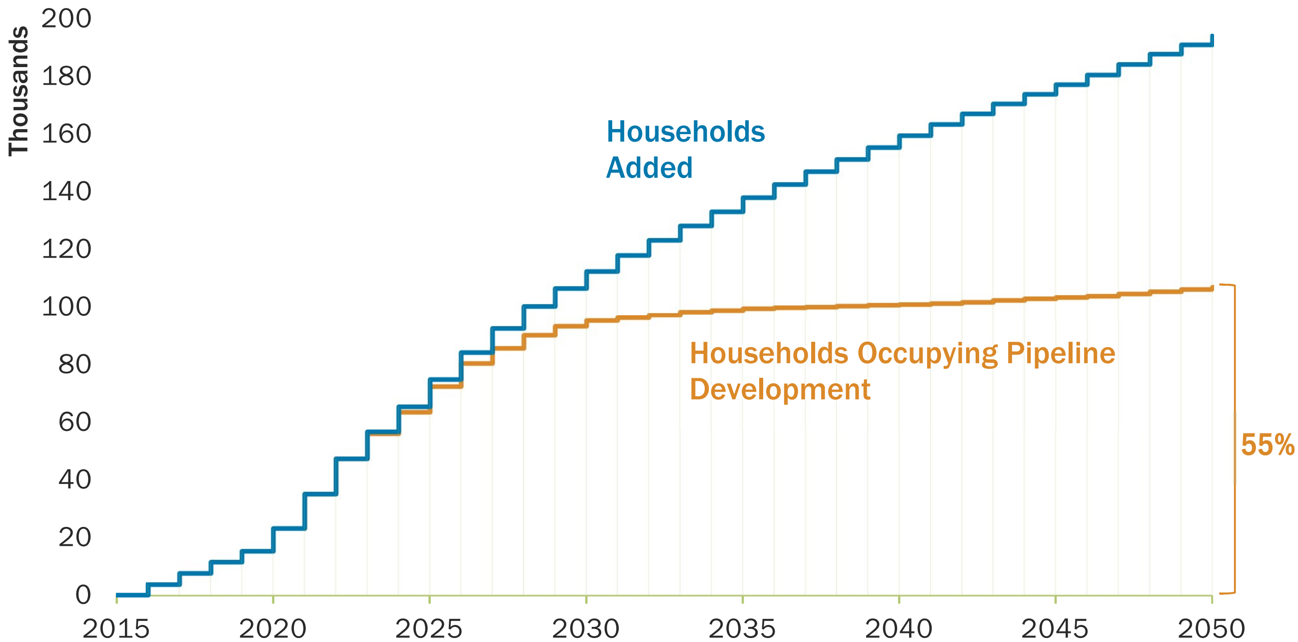


Figure 5: Commercial Development in Forecast's Real Estate Development Pipeline

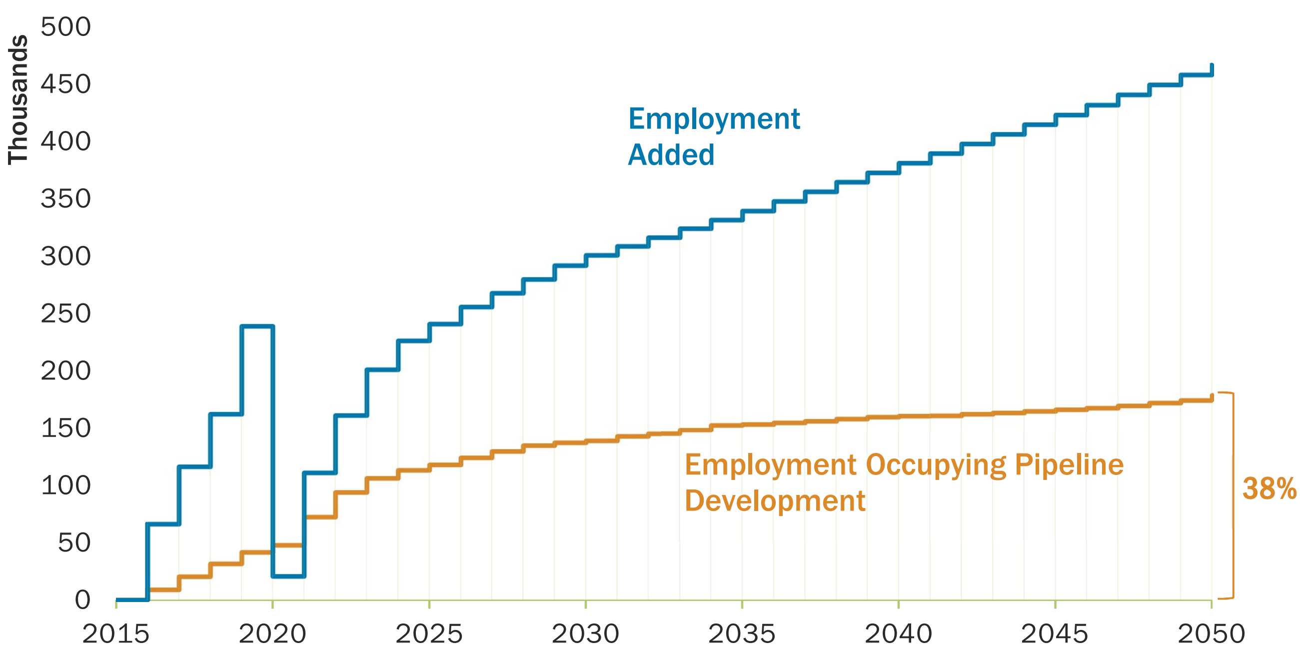
Figures 6 and 7 show the significant role the real estate pipeline had in allocating future growth. Particularly, for household growth, where 55 percent of new households added in the forecast selected blocks with newly built units.

Figure 6: Share of Forecasted Households Added Due to Residential Pipeline Projects by Year



Source: DVRPC 2021

Figure 7: Share of Forecasted Employment Added Due to Nonresidential Pipeline Projects by Year



Source: DVRPC 2021

Two-Phased Forecasting and Review

The forecast began in 2020 and 2021, the 2015 base year was quite distant compared to the prior forecast with the same base year, even though a decennial census count was still unavailable for a base. DVRPC staff worked to conform the early years in the forecast period to known observed data. The UrbanSim model allowed DVRPC and partners to focus first on forecasting to 2019 to achieve results reflecting years that were then in the past, then lock in a 2019 base model year for testing 2020 to 2050 simulations.

2015–2019 "Forecast"

Observed data was used to keep modeled results in close proximity to observed data sources as much as possible:

- these sources for 2015 to 2019 totals by county, and sometimes municipal/district geographies were used in:
  - household and employment control totals;
  - model calibration; and
- household and employment relocation models were employed to allow declines in some areas.

SLUAC members reviewed preliminary 2019 results and gave feedback to DVRPC staff. Despite the nearness of the modeled result in many aspects, all agreed it best to improve the fit to data sources by employing a post-processing procedure to randomly select households and employment in geographies exceeding source totals and moving them to geographies where the modeled result fell short.

Finalizing the 2015 and 2019 zonal results allowed the travel model team to calibrate and validate the travel model with a new 2019 base year.

While much was done to ensure conformity with observed data, even the "observed" sources were often estimates based on the best available data. PEP releases and the later Decennial count proved how divergent results from two different demographic data collection efforts could be. This is demonstrated in Table 3, with the 2019 PEP Release 2015–2019 population estimates, followed by the 2020 Decennial Census count. The sparkline graphs for each geography show how counter to the estimated annual PEP trends the Decennial count was. Such a drastic change would not have happened in one year, so the PEP must have been missing some of the change dynamics that followed the 2010 Census.

Additionally, little was known in any detail or certainty of what conditions were at small geographies like census blocks prior to the 2020 Census. UrbanSim offers a modeled translation of information reported at higher geographies to small areas of the region.

Table 3: Comparison of U.S. Census Bureau Observed Population Sources

Year	2019 PEP Estimates 2015	2016	2017	2018	2019	Decennial Census	Sparkline
Burlington	446,832	445,972	445,610	444,745	445,349	461,860	
Camden	507,638	507,002	506,224	506,353	506,471	523,485	
Gloucester	290,943	290,761	290,961	291,525	291,636	302,294	
Mercer	368,124	367,699	368,168	368,188	367,430	387,340	
Four New Jersey Counties	1,613,537	1,611,434	1,610,963	1,610,811	1,610,886	1,674,979	
Bucks	625,276	625,861	626,811	627,812	628,270	646,538	
Chester	515,055	516,767	518,901	522,086	524,989	534,413	
Delaware	563,225	563,708	563,858	565,231	566,747	576,830	
Montgomery	817,180	819,791	824,303	826,924	830,915	856,553	
Philadelphia	1,571,065	1,576,051	1,580,601	1,583,592	1,584,064	1,603,797	
Five Pennsylvania Counties	4,091,801	4,102,178	4,114,474	4,125,645	4,134,985	4,218,131	
DVRPC Region	5,705,338	5,713,612	5,725,437	5,736,456	5,745,871	5,893,110	

Source: U.S. Census Bureau's Population Estimates Program (2019 Release), and 2020 Decennial Census

2019–2050 Forecast

With a modeled, observed data-conforming 2019 base year established, DVRPC staff began forecasting out to the 2050 forecast horizon year. SLUAC members were asked to give feedback on the prior DVPRC 2045 forecast's municipal- and district-level results. Members noted where expectations for growth had diverged from the prior forecast round and where they wound up the same. Testing how different configurations impacted model results informed the process of creating municipal and district targets that fit to county 2050 targets.

Staff ensured the latest available CoStar data was reflected in the real estate development pipeline. SLUAC members were able to place comments at points in the UrbanCanvas viewer map to ensure important development projects were included in the pipeline. Video calls were conducted one-on-one with each county to: ensure no significant projects were missed, clarify DVRPC staff questions about project comments, and ensure the important growth locations were noted so model performance could be monitored to ensure reasonable results.

Targets helped DVRPC staff troubleshoot model specifications. For example, when municipal growth was too high, block-level residential unit and employment capacity were decreased. Staff iterated by making various changes and then running the model for one or several concurrent simulations (each taking 5 to 6 hours) with varying configurations to see which version performed the best—calibrated or uncalibrated simulations and regional or subregional control totals were all tested in various combinations.

Fall-back measures

The UrbanSim platform has a failsafe function, called Adjustments, to make changes that would be difficult for a model to predict. Although few, Adjustments were employed to move employment from the Philadelphia Police Department headquarters at the Round House at Race and 7th streets to a remodeled former Philadelphia Inquirer building on Broad Street in 2021. In the 2015–2019 forecast an Adjustment was used to move a state prison in Skippack Township in Montgomery County to an adjacent census block after a newly built facility was occupied and the prior correctional facility was closed in 2018. GQ population for the inmates were also moved within in the GQ table.

While the model creates a rational, sound method to replicate real world relationships and behaviors, models have limits. An additional tool provided by the UrbanSim team was the capability to apply “dummy” values to bolster or lessen the attractiveness of municipalities to HLCM and ELCM segments. When other means were exhausted to reach results in the realm of targets, testing combinations of positive or negative dummy values for certain municipalities helped augment the modeled results. Combined with other model configurations changes the iterative model simulations and assessments resembled a game of whack-a-mole, where limiting growth one place caused it to reappear somewhere else or making a place more attractive meant taking away some growth elsewhere.

Adoption and Use

Once model results were determined to be close enough to targets to then share with county partners, SLUAC members received draft results. After requests to revise targets for a handful of municipalities, a final round of model runs and modifications were performed until the new targets were met. At that point the results were brought before the Regional Technical Committee (RTC). The RTC recommended Board approval on June 8, 2021 and the Board approved it on June 24, 2021.

Following adoption, the zonal-level results were passed to the travel model team and conformity analysis travel model runs began. The forecast model scenario has been and will continue to be used and adapted with different development outcomes to compare to the adopted result for DVRPC studies.

For analyses looking to utilize DVRPC Board-adopted forecasts prior to the next update, one option is to take the change in population from 2020 to the future year of interest and add that amount to the 2020 Census figures.

Conclusion

Updated forecasting methods, including a modeled allocation of change in travel model zones due to simulations of real-world supply and demand, in combination with block-level capacity constraints, greatly augments the DVRPC forecast, travel model inputs, and analytical capabilities of the agency. The detailed information required by the travel model at the zonal level is further enhanced with more probable outcomes because households and employment locate based on what’s attractive or unattractive to certain demographic segments or employment sectors and built-out areas are too constrained for more growth. Municipal and county-level forecasts are informed by simulated, probable decision-making and individual real estate projects actually under construction or in planning stages.

Formation of, and engagement with, the SLUAC, including access to mapped model inputs and outputs and ability to markup the map interface with comments, furthers the collaborative nature of DVRPC forecast. Working with partners and providing modeled results for them to react to makes a better final product and model. SLUAC reality checks and local knowledge allow troubleshooting that continues to inspire model improvements.

PART II:

Forecast Results

Population Forecast

Table 3 summarizes DVRPC's adopted regional and county population forecasts in five-year increments through 2050. Municipal- and district-level forecasts are provided as a table in Appendix A. The Greater Philadelphia Region was forecasted to gain just over half a million new residents between 2015 and 2050, a gain of nearly 9 percent. County-level gains varied. This is demonstrated in the treemap graph in Figure 8. County rectangles are proportionate to their gain in size over the period. Chester County, Pennsylvania had the greatest absolute change of over 130,000 people, or 26 percent of the region's growth. Philadelphia and Montgomery County in Pennsylvania were in second and third place for gains, respectively. Combined, these three counties are expected to contribute more than two-thirds of regional growth over this period. Camden County, New Jersey was forecast to gain almost 12,000 new residents, a 2.3 percent increase, but was the least significant contributor to regional growth, at 2.4 percent share of regional growth.

By percentage change, the greatest county increase was Chester County, exceeding 25 percent. The next two percentage change rankings are Gloucester County with 12.5 percent and Montgomery County with 12.3 percent.

With 9 percent of the region's population in 2015 and 10.4 percent in 2050, Chester County was the only county to see more than half a percentage change in its share of the total regional population. It was also the only county to see a positive change in ranking for population size. Chester is expected to exceed Delaware County's population by 2030, however, it will still lag behind Philadelphia, Montgomery, and Bucks counties in the most populous rankings. Philadelphia's share of the region remains the highest and steady at 27 percent—nearly the same as all the region's New Jersey counties combined. Pennsylvania counties gain at a faster pace than New Jersey counties in the region, with 9.6 and 6.7 percent growth, respectively.

Figures 9 to 12 map various views of the population forecast by municipality and Philadelphia planning district. Figure 9 shows total 2050 population. Population is most concentrated in Philadelphia and the region's mature suburbs and along major highway corridors, including Route 422, Route 30, Mercer County's Route 1 corridor, and the Route 55 in Gloucester County and southern Camden County. Figure 10 shows the absolute change from base to horizon year, Figure 11 the percentage change for the period, and Figure 12 the density of the absolute change. While the absolute and percentage change maps show considerable differences in geographic clustering of growth, the density of absolute change more accurately shows the concentration of new population in the region, which tends to be in its urban core and mature suburbs and boroughs.

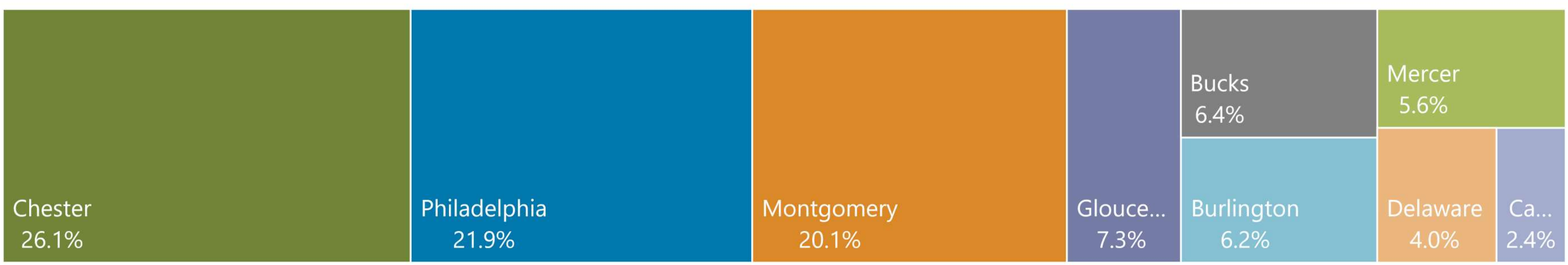
Table 4 shows the highest ranked counties for absolute growth between 2015 and 2050, and Table 5 shows the highest ranked for percentage change over the same period. Both tables feature a visualization of the timing within the forecast period in which the growth is expected to occur. Philadelphia's Central Planning District has the greatest absolute forecasted growth with a gain of nearly 48,000 people during the period. This is greater than the forecasted growth of the next three most highly ranked municipalities and districts (University – Southwest and Lower North districts, and Upper Merion Township) combined. With a percentage change of 32.2 percent, the Central district just barely fell outside of the top 20 percentage change rankings.

Table 4: Forecasted Population by County, 2015–2050

County	2015 Census Estimate	2019 Census Estimate*	2020 Forecast	2025 Forecast	2030 Forecast	2035 Forecast	2040 Forecast	2045 Forecast	2050 Forecast	2015–2050 Absolute Change	2015–2050 Percentage Change
Burlington	446,863	445,349	447,971	463,830	471,001	474,401	476,962	477,540	477,884	31,021	6.9%
Camden	507,692	506,472	507,378	512,630	512,790	515,571	518,525	519,127	519,476	11,784	2.3%
Gloucester	291,091	291,636	291,710	295,192	298,495	307,003	312,710	321,140	327,608	36,517	12.5%
Mercer	368,200	367,430	367,925	378,112	392,070	394,244	395,881	396,202	396,462	28,262	7.7%
Four New Jersey Counties	1,613,846	1,610,887	1,614,984	1,649,764	1,674,356	1,691,219	1,704,078	1,714,009	1,721,430	107,584	6.7%
Bucks	625,225	628,270	629,040	635,768	641,786	646,930	651,113	654,442	657,131	31,906	5.1%
Chester	515,043	524,989	528,218	563,468	586,300	604,007	620,391	634,119	645,673	130,630	25.4%
Delaware	563,142	566,747	566,610	570,207	573,667	576,903	579,706	581,763	583,376	20,234	3.6%
Montgomery	817,199	830,915	833,914	852,415	868,662	883,800	896,576	907,942	917,924	100,725	12.3%
Philadelphia	1,571,440	1,584,004	1,590,161	1,627,244	1,650,559	1,658,977	1,665,398	1,670,261	1,680,798	109,358	7.0%
Five Pennsylvania Counties	4,092,049	4,134,925	4,147,943	4,249,102	4,320,974	4,370,617	4,413,184	4,448,527	4,484,902	392,853	9.6%
DVRPC Region	**5,705,895**	**5,745,812**	**5,762,927**	**5,898,866**	**5,995,330**	**6,061,836**	**6,117,262**	**6,162,536**	**6,206,332**	**500,437**	**8.8%**

Source: DVRPC, 2021

Figure 8: County Share of Forecasted Regional Population Growth: 2015–2050



Source: DVRPC, 2021

Figure 9: 2050 Municipal and District Population Forecast

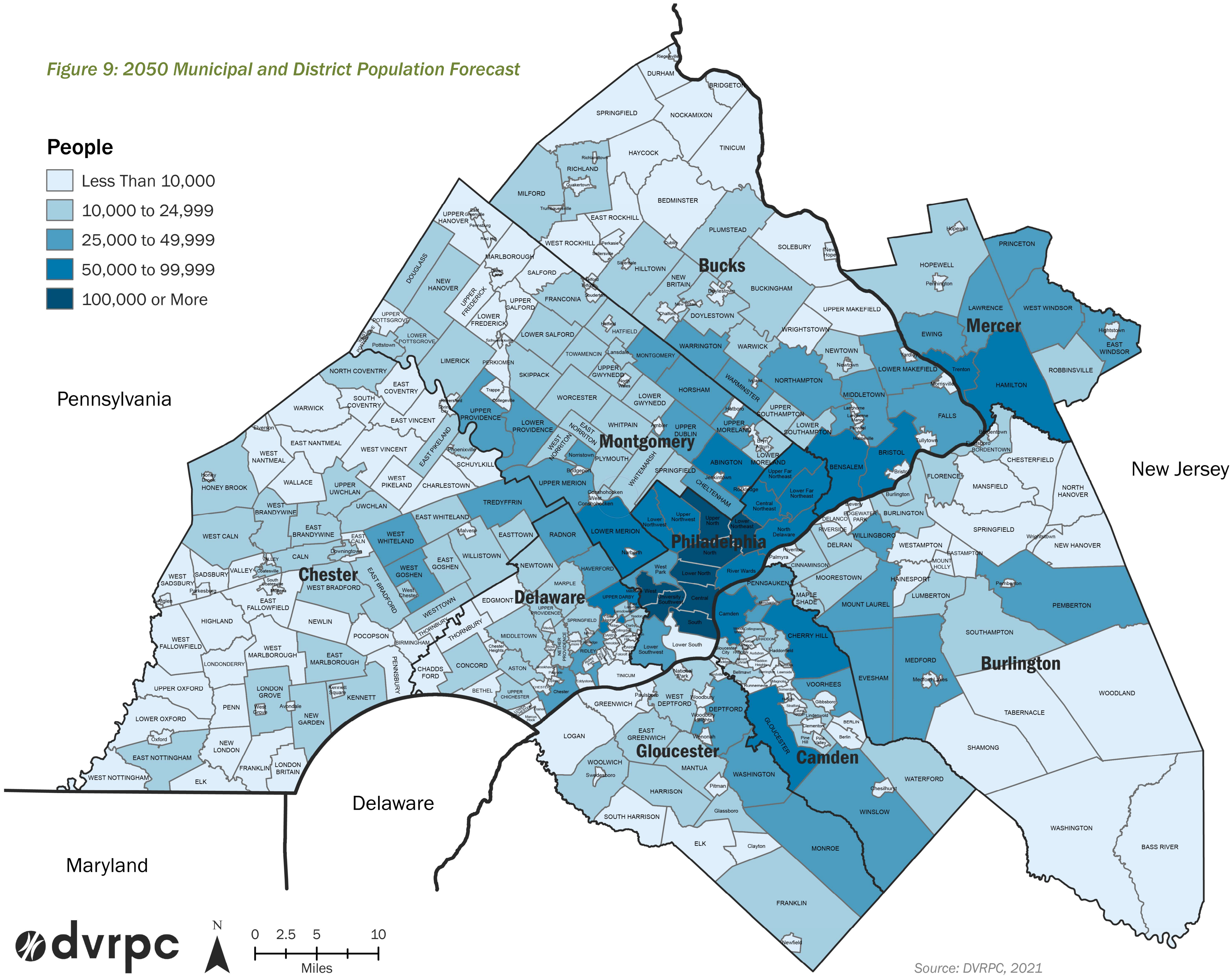


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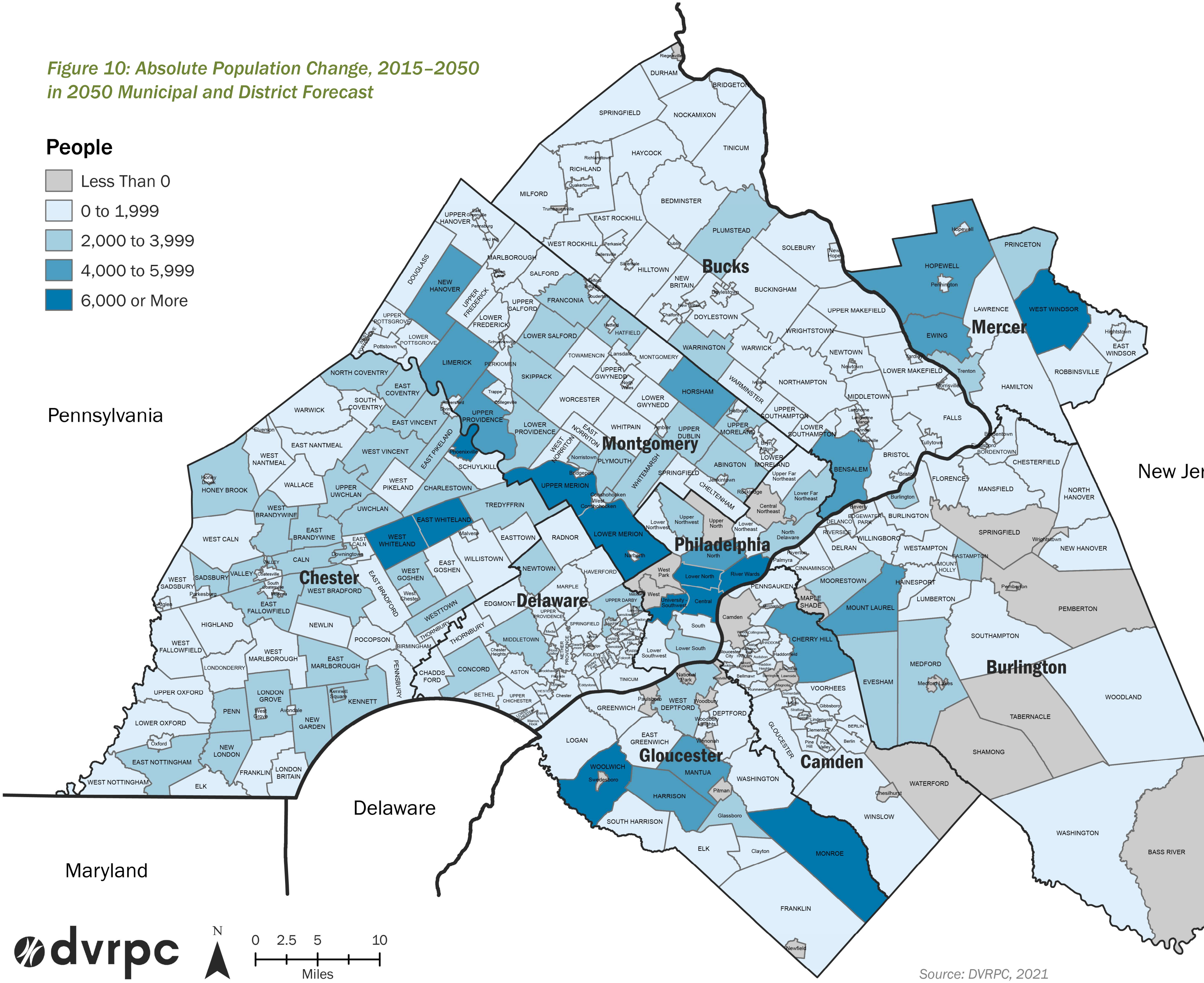
Figure 10: Absolute Population Change, 2015–2050 in 2050 Municipal and District Forecast



Source: DVRPC, 2021

Figure 11: Percentage Population Change, 2015–2050 in 2050 Municipal and District Forecast

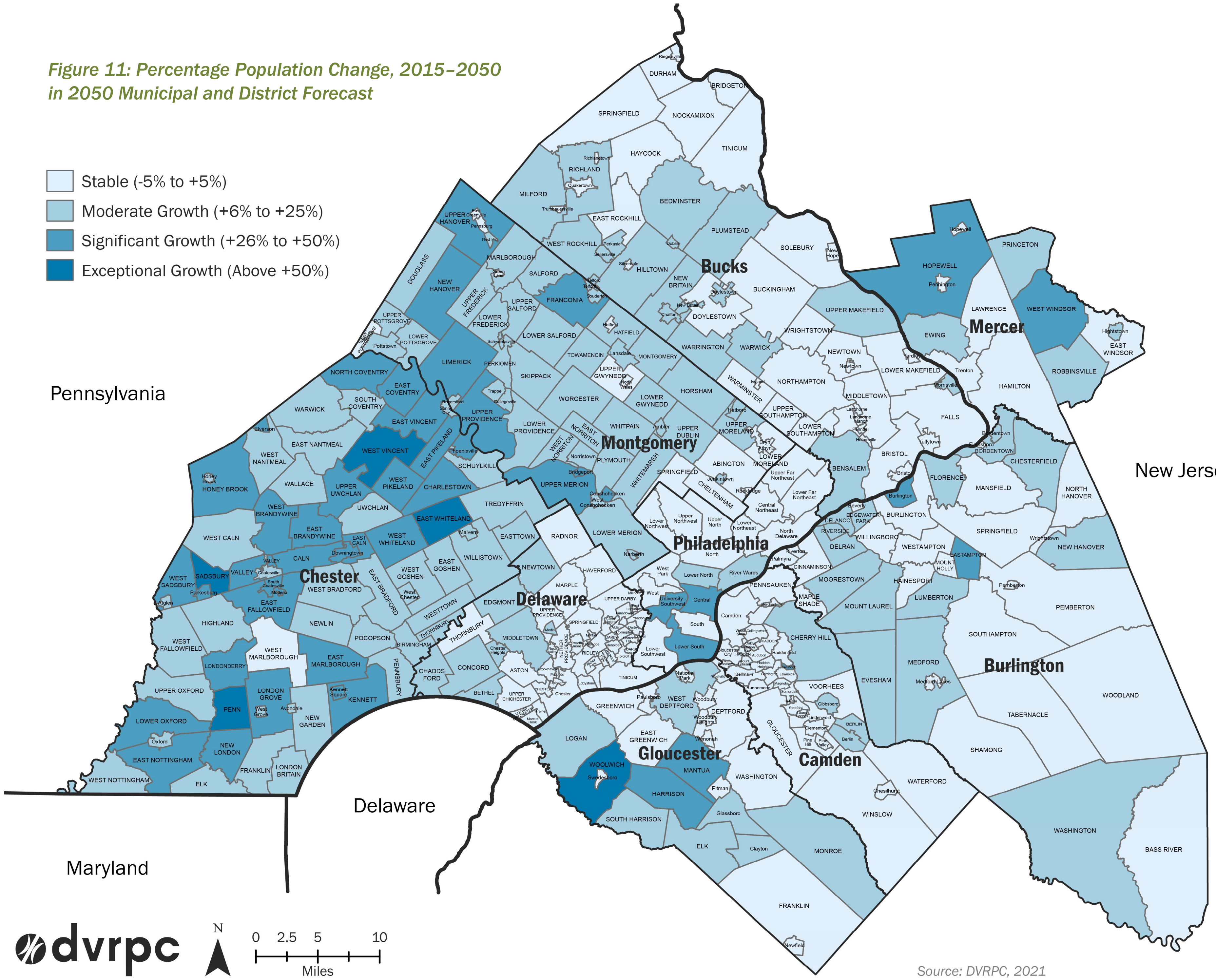
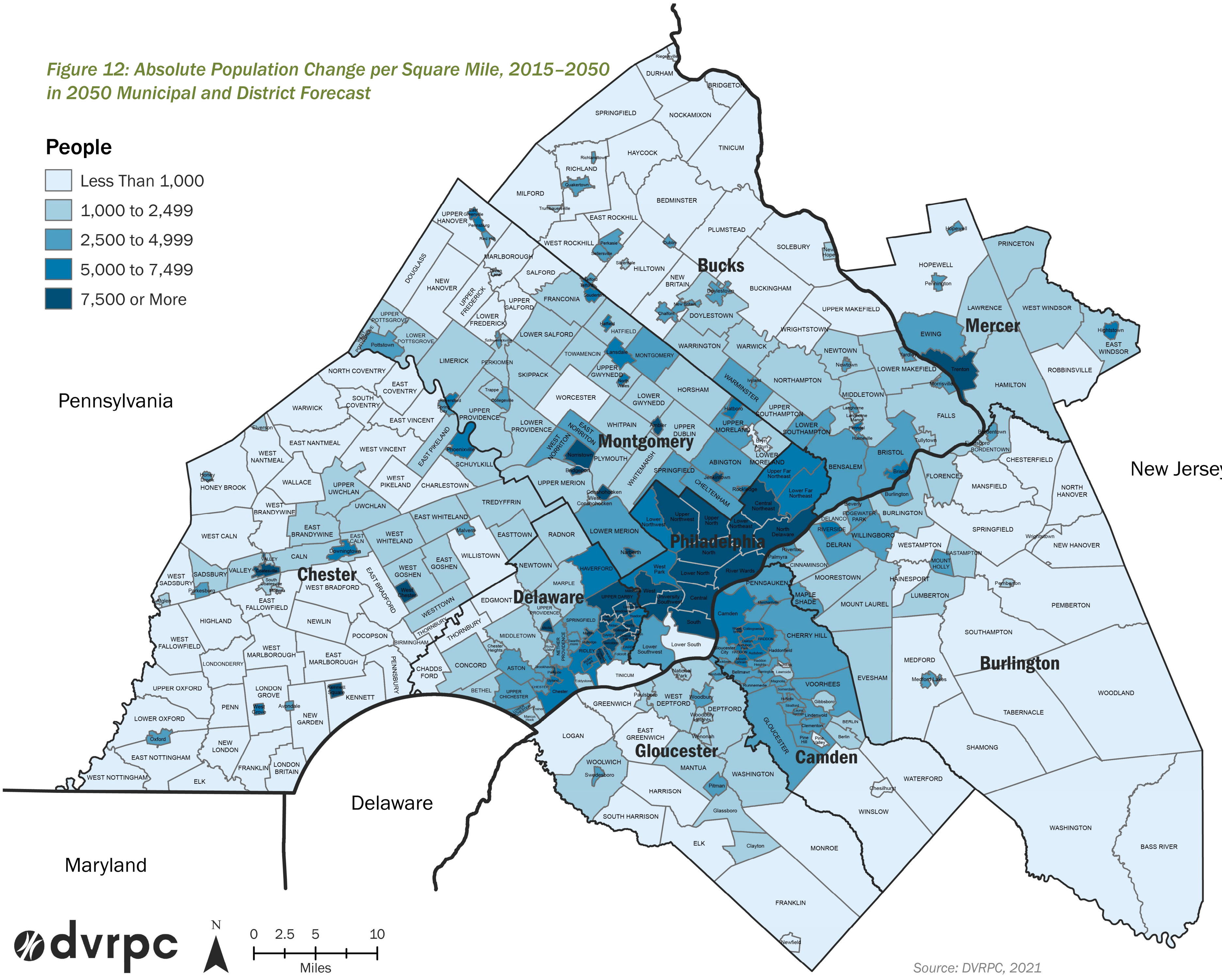


Figure 12: Absolute Population Change per Square Mile, 2015–2050 in 2050 Municipal and District Forecast



Source: DVRPC, 2021

Table 5: Municipalities and Districts with the Greatest Forecasted Absolute Change in Population, 2015–2050

			2015 – 2050		Phasing of Change by Five-Year Period						
Absolute Change Rank	Municipality or District	County	Absolute Change	Percentage Change	2015 – 2020	2020 – 2025	2025 – 2030	2030 – 2035	2035 – 2040	2040 – 2045	2045 – 2050
1	Central	Philadelphia	47,757	38.2%							
2	University - Southwest	Philadelphia	21,112	26.0%							
3	Lower North	Philadelphia	14,920	16.5%							
4	Upper Merion Township	Montgomery	9,495	33.3%							
5	Woolwich Township	Gloucester	9,398	76.7%							
6	West Windsor Township	Mercer	9,183	32.8%							
7	West Whiteland Township	Chester	9,045	49.1%							
8	River Wards	Philadelphia	8,766	12.6%							
9	Monroe Township	Gloucester	7,799	21.2%							
10	Lower Merion Township	Montgomery	7,024	12.0%							
11	Phoenixville Borough	Chester	6,911	41.4%							
12	East Whiteland Township	Chester	6,195	58.4%							
13	New Hanover Township	Montgomery	5,979	48.0%							
14	Upper Providence Township	Montgomery	5,972	25.6%							
15	Cherry Hill Township	Camden	5,226	7.4%							
16	Limerick Township	Montgomery	5,063	27.1%							
17	Harrison Township	Gloucester	5,015	38.9%							
18	Horsham Township	Montgomery	4,826	18.2%							
19	Hopewell Township	Mercer	4,636	25.2%							
20	Bensalem Township	Bucks	4,399	7.3%							

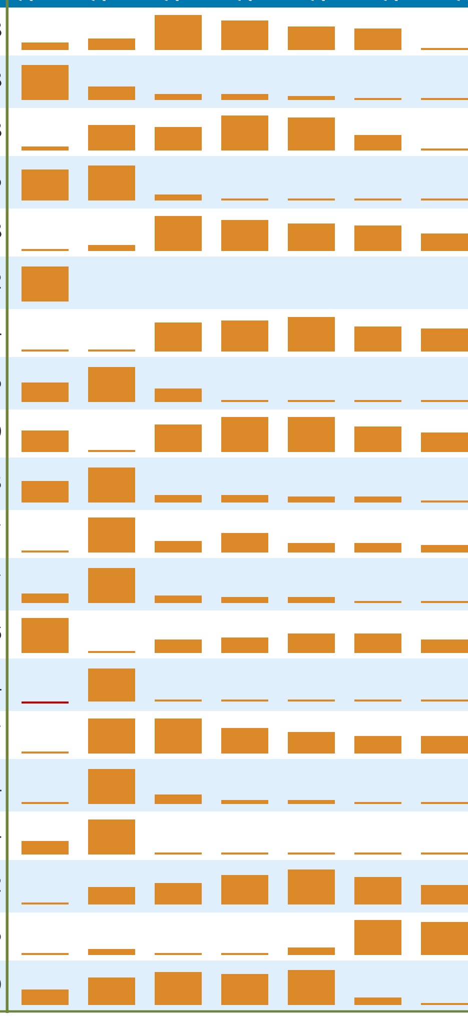
Source: DVRPC, 2021

Six locations made both top 20 lists due to regionally significant absolute change and locally significant percentage change. These are:

- Woolwich Township in Gloucester County (absolute rank = 5, percentage rank = 1);
- West Whiteland Township in Chester County (absolute rank = 7, percentage rank = 8);Phoenixville Borough in Chester County (absolute rank = 11, percentage rank = 16);
- East Whiteland Township in Chester County (absolute rank = 12, percentage rank = 4);
- New Hanover Township in Montgomery County (absolute rank = 13, percentage rank = 9); and
- Harrison Township in Gloucester County (absolute rank = 17, percentage rank = 19);

Table 6: Municipalities and Districts with the Greatest Forecasted Percentage Change in Population, 2015–2050

Percentage Change Rank	Municipality or District	County	2015 – 2050 Percentage Change	2015 – 2050 Absolute Change	Phasing of Change by Five-Year Period: 2015 - 2020	2020 - 2025	2025 - 2030	2030 - 2035	2035 - 2040	2040 - 2045	2045 - 2050
1	Woolwich Township	Gloucester	76.7%	9,398							
2	West Vincent Township	Chester	69.2%	3,478							
3	Sadsbury Township	Chester	64.7%	2,508							
4	East Whiteland Township	Chester	58.4%	6,195							
5	Penn Township	Chester	51.3%	2,828							
6	Tavistock Borough	Camden	50.0%	2							
7	West Sadsbury Township	Chester	49.7%	1,224							
8	West Whiteland Township	Chester	49.1%	9,045							
9	New Hanover Township	Montgomery	48.0%	5,979							
10	East Brandywine Township	Chester	44.6%	3,693							
11	East Marlborough Township	Chester	43.8%	3,187							
12	East Vincent Township	Chester	43.6%	3,017							
13	Charlestown Township	Chester	43.3%	2,436							
14	Downingtown Borough	Chester	43.1%	3,421							
15	West Brandywine Township	Chester	41.7%	3,117							
16	Phoenixville Borough	Chester	41.4%	6,911							
17	Lower South	Philadelphia	40.1%	2,234							
18	Elverson Borough	Chester	39.9%	522							
19	Harrison Township	Gloucester	38.9%	5,015							
20	East Pikeland Township	Chester	38.8%	2,839							



Source: DVRPC, 2021

Tavistock Borough in Camden County is ranked 6 for percentage change rank, even though it is only forecast to gain two people from its 2015 estimate of four, resulting in a 50 percent increase. It is anticipated to remain the region's smallest municipality. Also, Lower South appears 17th in the percentage change rankings, as the lifting of residential prohibitions in the Navy Yard will significantly increase a district more known as a home to ports, logistics, and employment centers.

Phasing of regional population growth through the forecast period tended to be higher in the front half or the period and slower over the last half. Phasing at the subcounty level varied, as demonstrated by both top 20 lists. Some had quick gains then went down to barely any growth. Hopewell Township in Mercer County saw population loss over the first five years of the forecast, only to rebound quite a bit the adjacent five years, then tapering to almost no gains by 2035. Some like Harrison Township aren't forecasted to grow significantly until the 2040s.

Employment Forecast

Table 6 summarizes DVRPC's adopted regional and county employment forecasts in five-year increments through 2050, and municipal-level employment forecasts are provided in Appendix B. The Greater Philadelphia Region's employment was forecasted to increase by nearly 467,000 between 2015 and 2050, a gain of over 15 percent.

Overall, employment gains over the forecast period were strikingly close to the 500,000 person gain in the population forecast of the same period—a rare occurrence, as much of the population added would not be of a working age. However, this is best explained in the context of the trends of the 2010s discussed earlier under control total development. While population was growing slowly (0.7 percent) from 2015 to 2019, employment increased by nearly 8 percent leading to record low unemployment rates and the strong recovery and growth out of the Great Recession. Then 2020 erased nearly all the regional employment gains of the prior four years in just one year—more than half the counties (Burlington, Camden, Bucks, Chester, and Montgomery) had 2020 employment totals drop below their 2015 totals. Due to that drop, the 31-year regional employment gain from 2019 to 2050 of 6.9 percent was less than the 2015 to 2019 increase. Percentage population gains over the 2019 to 2050 period were more on par with employment, at 8 percent, but the absolute increase of 460,500 new residents was a little more than twice employment's gains of 227,500—a much more typical phenomenon over a forecasted period.

Figure 13 is a treemap showing county shares of regional employment growth. Philadelphia is forecasted to be the largest contributor to regional employment growth from 2015 to 2050. Its 30 percent share nearly equaled the next highest contributors, Montgomery (16 percent share) and Chester (15 percent share), combined. The remaining 39 percent of regional growth is forecast to be fairly evenly distributed amongst the rest of the region's counties. Gloucester had the highest in the group—a 7.5 percent share—and Camden and Bucks had the lowest, each with a 6 percent share of regional growth.

Figures 14 to 17 map various views of the employment forecast by municipality and planning area. Figure 14 shows total 2050 employment, Figure 15 the absolute change from base to horizon year, Figure 16 the percentage change for the period, and Figure 17 the density of the absolute change. The density of employment change had a somewhat similar distribution to population change density. It tends to increase in the region's core and where existing employment is already in place. The top 20 rankings for absolute and percentage growth are found in tables 8 and 9, respectively. There were only three locations making both lists:

- University – Southwest (absolute rank = 1, percentage rank =13);
- Lower South (absolute rank = 2, percentage rank =1); and
- Florence Township (absolute rank = 18, percentage rank =3);

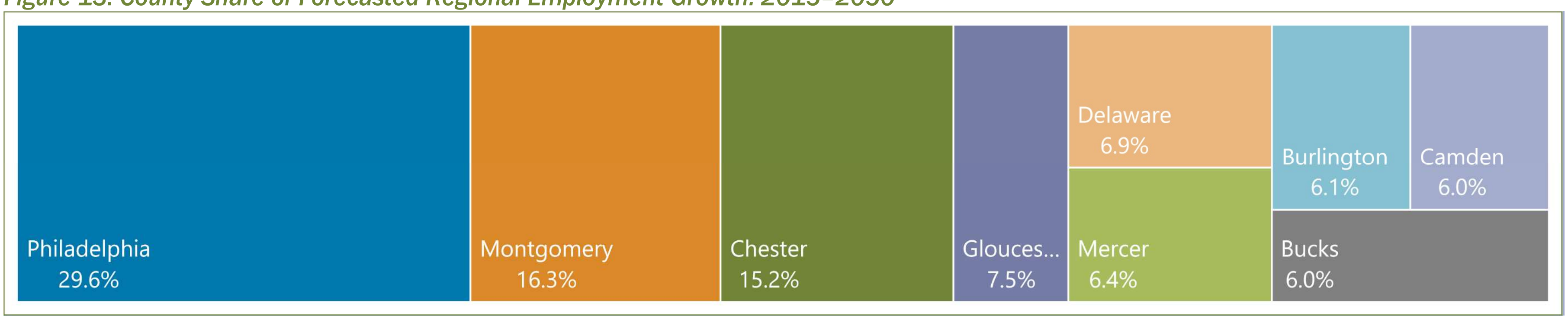
Regionally, the employment forecast's trendline was more tumultuous than the population forecast, as seen in Figure 5 (Figure 4's household growth is a fair proxy for the population forecast for comparison sake). The phasing of growth in these top 20 lists shows a good number of municipalities with negative or flat growth due to the quick gains then even quicker losses of the 2015–2020 period. However, quite a few had significant net gains even to 2020. Most had significant gains between 2020 and 2025. Only a few experienced significant growth in the later years of the forecast. Looking at the three that made the rankings in both lists, University – Southwest, and Lower South saw gains in later years. However, University-Southwest projected slower growth in the middle years then spikes up at the end of the forecast due to development over the rail yard proposed to be capped north of 30th Street Station. Lower South saw continued growth throughout, increasing later on with the completion of the Navy Yard master plan. Florence Township had significant growth in the early forecast due to growth in distribution centers, including a very large Amazon facility in 2018, but essentially flatlined with build-out in later years—sometimes with small losses.

Table 7: Forecasted Employment by County, 2015–2050

County	2015 NETS	2019 Base*	2020 Forecast	2025 Forecast	2030 Forecast	2035 Forecast	2040 Forecast	2045 Forecast	2050 Forecast	2015–2050 Absolute Change	2015–2050 Percentage Change
Burlington	243,773	258,237	241,044	259,622	263,784	265,316	267,490	269,911	272,016	28,243	11.6%
Camden	235,055	249,243	231,475	251,236	254,730	256,495	258,893	261,276	263,284	28,229	12.0%
Gloucester	116,906	132,468	123,027	138,978	142,306	144,046	146,652	149,362	151,891	34,985	29.9%
Mercer	229,501	244,636	230,526	246,875	249,634	251,430	254,122	256,973	259,402	29,901	13.0%
Four New Jersey Counties	825,235	884,584	826,072	896,711	910,454	917,287	927,157	937,522	946,593	121,358	14.7%
Bucks	315,665	334,841	308,713	326,700	332,639	335,324	338,108	341,149	343,632	27,967	8.9%
Chester	302,656	322,898	298,305	336,321	345,083	351,403	358,837	366,724	373,664	71,008	23.5%
Delaware	261,417	277,473	262,851	279,772	283,398	285,407	288,280	291,175	293,526	32,109	12.3%
Montgomery	567,585	605,989	559,413	601,014	610,266	616,333	625,549	635,373	643,790	76,205	13.4%
Philadelphia	766,163	852,244	804,345	839,480	857,981	872,566	882,135	889,907	904,311	138,148	18.0%
Five Pennsylvania Counties	2,213,486	2,393,445	2,233,627	2,383,287	2,429,367	2,461,033	2,492,909	2,524,328	2,558,923	345,437	15.6%
DVRPC Region	3,038,721	3,278,029	3,059,699	3,279,998	3,339,821	3,378,320	3,420,066	3,461,850	3,505,516	466,795	15.4%

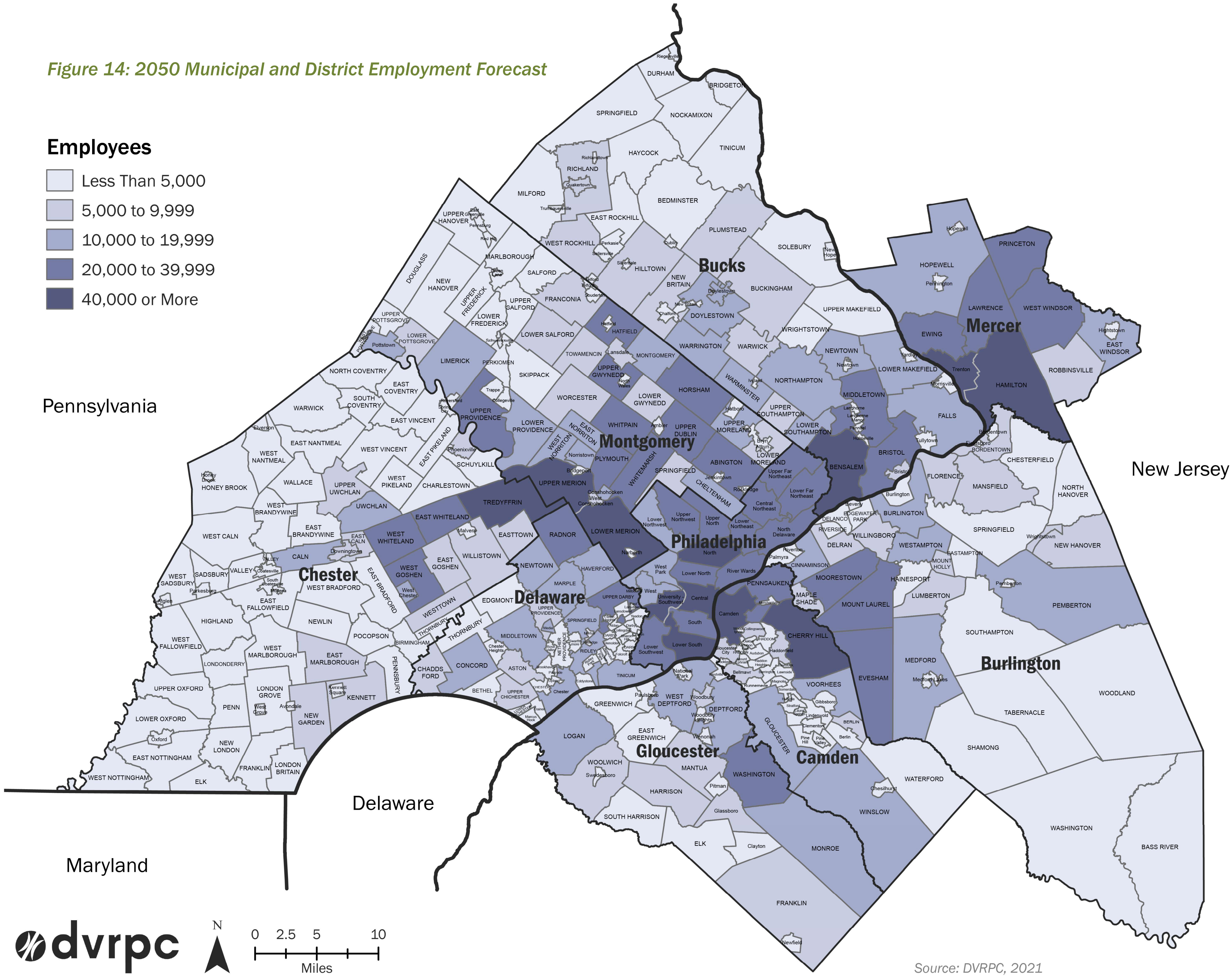
Source: DVRPC, 2021

Figure 13: County Share of Forecasted Regional Employment Growth: 2015–2050



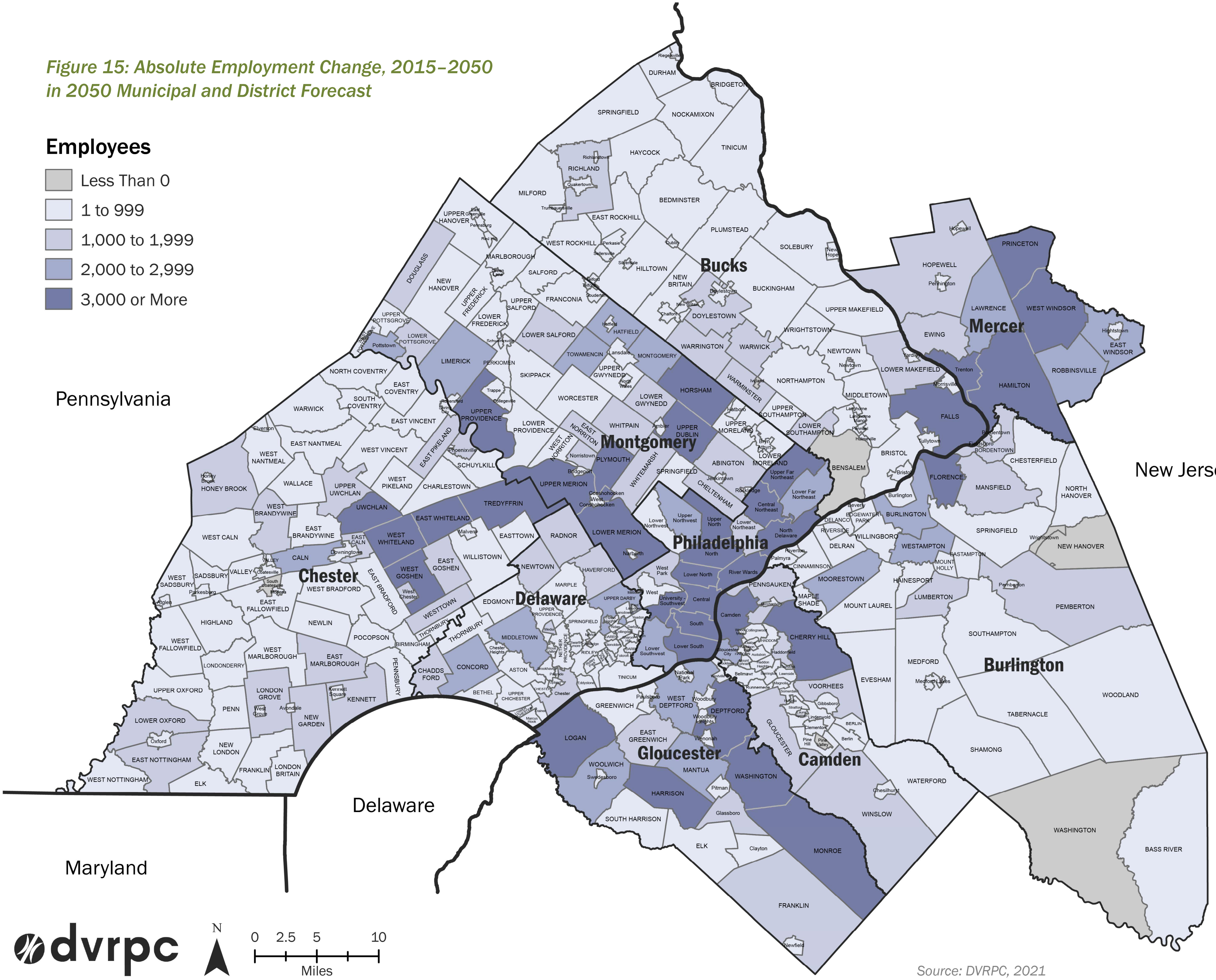
Source: DVRPC, 2021

Figure 14: 2050 Municipal and District Employment Forecast



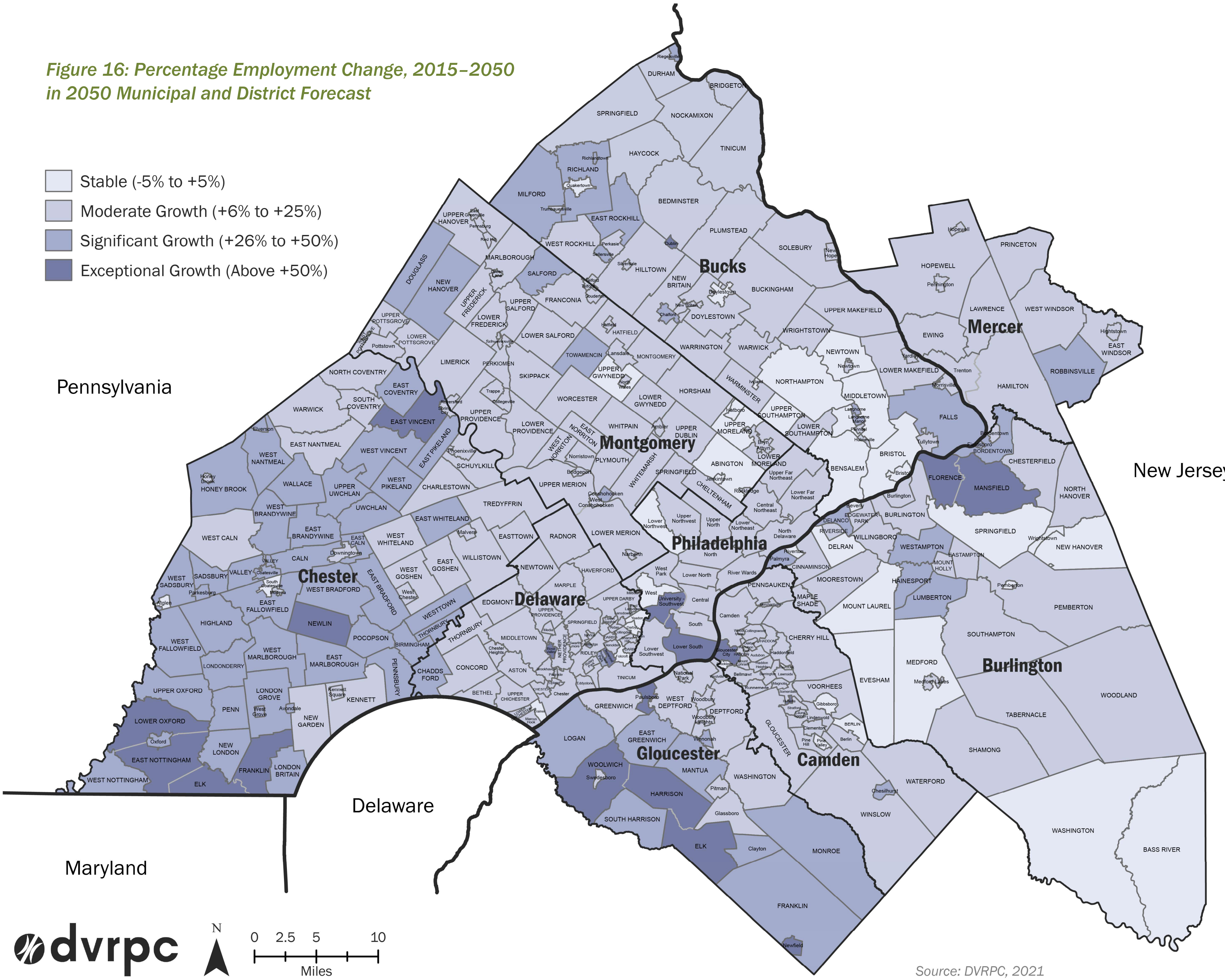
Source: DVRPC, 2021

Figure 15: Absolute Employment Change, 2015–2050 in 2050 Municipal and District Forecast



Source: DVRPC, 2021

Figure 16: Percentage Employment Change, 2015–2050 in 2050 Municipal and District Forecast



Source: DVRPC, 2021

Figure 17: Absolute Employment Change per Square Mile, 2015–2050 in 2050 Municipal and District Forecast

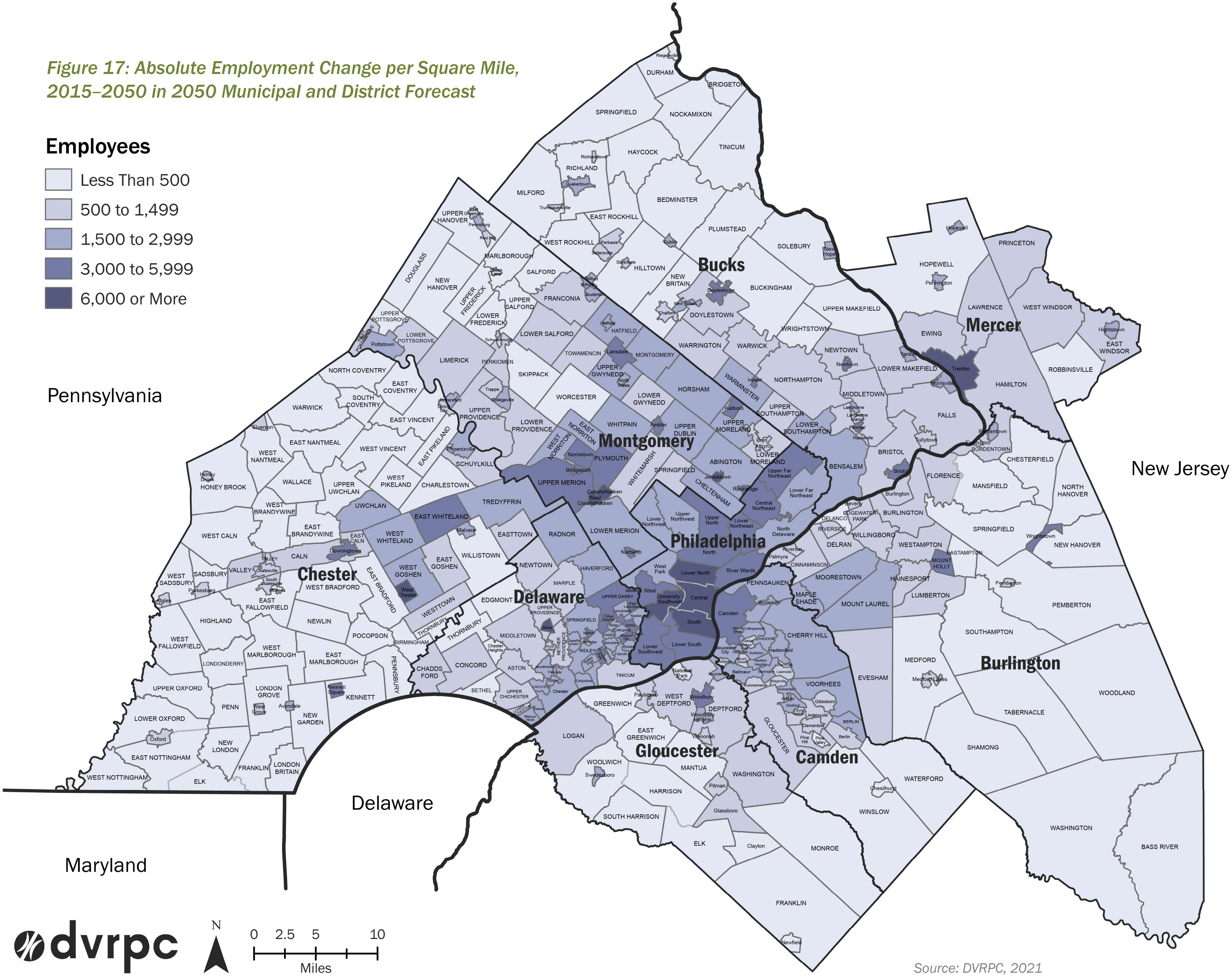
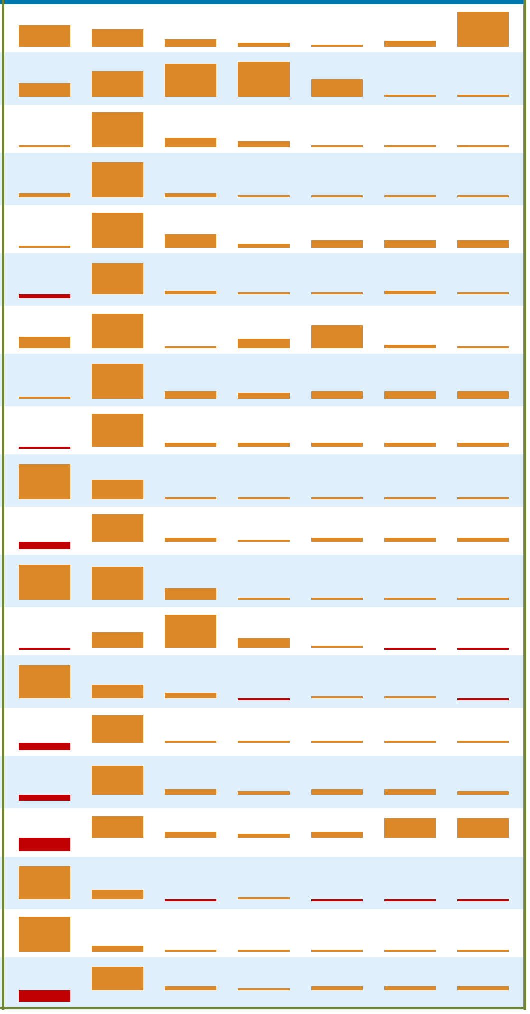


Table 8: Municipalities and Districts with the Greatest Forecasted Absolute Change in Employment, 2015–2050

Absolute Change Rank	Municipality or District	County	2015 – 2050 Absolute Change	2015 – 2050 Percentage Change	Phasing of Change by Five-Year Period: 2015 – 2020	2020 – 2025	2025 – 2030	2030 – 2035	2035 – 2040	2040 – 2045	2045 – 2050
1	University - Southwest	Philadelphia	47,870	58.4%							
2	Lower South	Philadelphia	25,687	132.4%							
3	Central	Philadelphia	20,263	7.7%							
4	Camden City	Camden	9,445	23.8%							
5	Upper Merion Township	Montgomery	8,396	16.0%							
6	East Whiteland Township	Chester	7,520	29.2%							
7	Lower Merion Township	Montgomery	6,416	11.8%							
8	Tredyffrin Township	Chester	6,412	12.4%							
9	Hamilton Township	Mercer	6,019	14.3%							
10	Upper Far Northeast	Philadelphia	5,354	17.6%							
11	West Windsor Township	Mercer	5,033	15.1%							
12	South	Philadelphia	5,018	15.0%							
13	Falls Township	Bucks	4,761	31.7%							
14	River Wards	Philadelphia	4,648	20.5%							
15	West Whiteland Township	Chester	4,626	21.5%							
16	Plymouth Township	Montgomery	4,461	19.7%							
17	Horsham Township	Montgomery	4,454	14.2%							
18	Florence Township	Burlington	4,301	90.1%							
19	Upper North	Philadelphia	4,194	13.8%							
20	West Goshen Township	Chester	4,159	16.7%							



Source: DVRPC, 2021

Conclusion

- From over the 35-year span of the forecast to 2050, the region is expected to gain half a million people and nearly as many jobs, bringing total population to over 6.2 million and total employment to more than 3.5 million.
- Chester County's growth will make it over take Delaware County as the fourth largest by population and Bucks County as the third largest by employment in the region.
- Led by Philadelphia, Montgomery, and Chester Counties, population and employment growth are greatest in the region's five Pennsylvania counties in both absolute and percentage change.
- Montgomery County had the highest count of municipalities or districts (five municipalities) in the top 20 absolute growers in population. Philadelphia had the highest count (seven districts) of top 20 absolute employment growers.

Table 9: Municipalities and Districts with the Greatest Forecasted Percentage Change in Employment, 2015–2050

Percentage Change Rank	Municipality or District	County	2015 – 2050 Percentage Change	2015 – 2050 Absolute Change	Phasing of Change by Five-Year Period: 2015 - 2020	2020 - 2025	2025 - 2030	2030 - 2035	2035 - 2040	2040 - 2045	2045 - 2050
1	Lower South	Philadelphia	132.4%	25,687							
2	Hi-Nella Borough	Camden	97.1%	202							
3	Florence Township	Burlington	90.1%	4,301							
4	Woolwich Township	Gloucester	89.2%	2,584							
5	Harrison Township	Gloucester	81.6%	3,056							
6	Elk Township	Chester	80.7%	326							
7	Norwood Borough	Delaware	71.8%	792							
8	Rose Valley Borough	Delaware	69.8%	194							
9	East Nottingham Township	Chester	68.3%	1,146							
10	Elk Township	Gloucester	66.7%	695							
11	Lower Oxford Township	Chester	64.5%	1,211							
12	Mansfield Township	Burlington	60.2%	1,985							
13	University - Southwest	Philadelphia	58.4%	47,870							
14	Dublin Borough	Bucks	58.0%	426							
15	Newfield Borough	Gloucester	54.6%	255							
16	East Vincent Township	Chester	53.2%	971							
17	Gloucester City	Camden	53.1%	2,032							
18	Paulsboro Borough	Gloucester	51.4%	924							
19	Newlin Township	Chester	51.2%	145							
20	Franklin Township	Chester	51.2%	377							

Source: DVRPC, 2021

- Chester County dominated the top 20 municipalities or districts with regard to percentage change in population with 15 municipalities making the list. With six top 20 percentage change municipalities for employment, it nudged out Gloucester County, which had 5 municipalities on the list.
- While generally slight, 33 municipalities and districts are predicted to decline in population over the forecast period, while only 8 locations expect employment decline

Appendix A

Forecasted Population by Municipality and District, 2015–2050

DELAWARE VALLEY
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REGIONAL
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Appendix A: Forecasted Population by Municipality and District, 2015–2050

Table A-1: Burlington County Forecasted Population by Municipality, 2015–2050

											2015-2050	
		2015	2019	2020	2025	2030	2035	2040	2045	2050	Absolute	Percentage
ID	Municipality or District	Base	Forecast	Forecast	Forecast	Forecast	Forecast	Forecast	Forecast	Forecast	Change	Change
3400503370	Bass River Township	1,438	1,416	1,416	1,416	1,417	1,425	1,430	1,432	1,432	-6	-0.4%
3400505740	Beverly City	2,509	2,479	2,479	2,479	2,479	2,488	2,501	2,503	2,503	-6	-0.2%
3400506670	Bordentown City	3,838	3,792	3,792	4,603	4,603	4,626	4,652	4,654	4,658	820	21.4%
3400506700	Bordentown Township	11,810	11,914	11,914	13,474	13,482	13,527	13,618	13,635	13,639	1,829	15.5%
3400508920	Burlington City	9,786	9,858	9,856	10,297	12,300	12,380	12,444	12,448	12,454	2,668	27.3%
3400508950	Burlington Township	22,664	22,594	22,547	22,705	22,842	22,930	23,015	23,036	23,048	384	1.7%
3400512670	Chesterfield Township	7,493	7,573	7,573	8,250	8,420	8,453	8,474	8,481	8,481	988	13.2%
3400512940	Cinnaminson Township	16,558	16,342	16,646	17,092	17,099	17,192	17,280	17,300	17,307	749	4.5%
3400517080	Delanco Township	4,501	4,430	4,496	4,795	4,799	4,836	4,855	4,857	4,858	357	7.9%
3400517440	Delran Township	16,725	16,492	16,566	17,925	18,293	18,381	18,469	18,500	18,514	1,789	10.7%
3400518790	Eastampton Township	5,921	6,144	6,656	8,048	8,048	8,077	8,115	8,123	8,133	2,212	37.4%
3400520050	Edgewater Park Township	8,772	8,647	8,647	9,085	9,183	9,248	9,310	9,320	9,321	549	6.3%
3400522110	Evesham Township	45,304	45,188	45,701	47,250	47,262	47,539	47,749	47,815	47,864	2,560	5.7%
3400523250	Fieldsboro Borough	539	552	552	552	552	554	557	557	557	18	3.3%
3400523850	Florence Township	12,644	12,486	12,592	13,003	13,332	13,384	13,431	13,439	13,445	801	6.3%
3400529010	Hainesport Township	6,035	5,976	5,976	5,995	5,999	6,154	6,263	6,293	6,316	281	4.7%
3400542060	Lumberton Township	12,360	12,192	12,183	12,962	13,550	13,613	13,695	13,709	13,727	1,367	11.1%
3400543290	Mansfield Township	8,574	8,533	8,533	8,634	8,745	8,844	8,932	8,959	8,984	410	4.8%
3400543740	Maple Shade Township	18,842	18,476	18,458	18,476	18,489	18,588	18,661	18,676	18,693	-149	-0.8%
3400545120	Medford Township	23,261	23,394	23,381	24,283	25,723	25,831	25,996	26,043	26,055	2,794	12.0%
3400545210	Medford Lakes Borough	4,052	3,914	3,914	3,914	3,914	3,928	3,946	3,950	3,950	-102	-2.5%
3400547880	Moorestown Township	20,430	20,516	20,493	21,539	23,089	24,021	24,189	24,231	24,243	3,813	18.7%
3400548900	Mount Holly Township	9,527	9,547	9,597	9,663	9,663	9,699	9,734	9,742	9,743	216	2.3%
3400549020	Mount Laurel Township	41,823	41,250	42,408	45,144	45,156	45,522	45,843	45,911	45,947	4,124	9.9%
3400551510	New Hanover Township	7,197	7,808	7,787	7,808	7,808	7,812	7,820	7,820	7,820	623	8.7%
3400553070	North Hanover Township	7,587	7,470	7,470	7,470	7,470	7,520	7,575	7,590	7,595	8	0.1%
3400555800	Palmyra Borough	7,253	7,140	7,140	7,140	7,450	7,486	7,529	7,535	7,545	292	4.0%

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ID	Municipality or District	2015 Base	2019 Forecast	2020 Forecast	2025 Forecast	2030 Forecast	2035 Forecast	2040 Forecast	2045 Forecast	2050 Forecast	2015-2050 Absolute Change	2015-2050 Percentage Change
3400557480	Pemberton Borough	1,352	1,324	1,324	1,324	1,324	1,325	1,325	1,325	1,327	-25	-1.8%
3400557510	Pemberton Township	27,522	26,979	26,966	26,979	26,982	27,060	27,172	27,201	27,235	-287	-1.0%
3400563510	Riverside Township	7,944	7,816	7,816	8,416	8,416	8,416	8,435	8,439	8,439	495	6.2%
3400563660	Riverton Borough	2,718	2,685	2,677	2,685	2,685	2,698	2,722	2,722	2,722	4	0.1%
3400566810	Shamong Township	6,436	6,367	6,367	6,367	6,367	6,401	6,416	6,418	6,421	-15	-0.2%
3400568610	Southampton Township	10,276	10,095	10,095	10,095	10,096	10,212	10,302	10,317	10,323	47	0.5%
3400569990	Springfield Township	3,328	3,257	3,257	3,257	3,257	3,263	3,276	3,283	3,284	-44	-1.3%
3400572060	Tabernacle Township	6,896	6,794	6,794	6,794	6,794	6,823	6,855	6,866	6,866	-30	-0.4%
3400577150	Washington Township	665	711	711	711	711	711	711	711	711	46	6.9%
3400578200	Westampton Township	8,658	8,649	8,649	8,649	8,649	8,723	8,819	8,821	8,836	178	2.1%
3400581440	Willingboro Township	31,034	32,005	32,005	32,007	32,009	32,151	32,275	32,307	32,317	1,283	4.1%
3400582420	Woodland Township	1,779	1,768	1,761	1,768	1,768	1,783	1,788	1,788	1,788	9	0.5%
3400582960	Wrightstown Borough	812	776	776	776	776	777	783	783	783	-29	-3.6%

Source: DVRPC, 2021

Table A-2: Camden County Forecasted Population by Municipality, 2015–2050

ID	Municipality or District	2015 Base	2019 Forecast	2020 Forecast	2025 Forecast	2030 Forecast	2035 Forecast	2040 Forecast	2045 Forecast	2050 Forecast	2015-2050 Absolute Change	2015-2050 Percentage Change
3400702200	Audubon Borough	8,686	8,637	8,637	8,637	8,637	8,661	8,684	8,690	8,699	13	0.1%
3400702230	Audubon Park Borough	1,004	1,002	1,002	1,002	1,002	1,002	1,008	1,013	1,013	9	0.9%
3400703250	Barrington Borough	6,758	6,642	6,642	6,645	6,648	6,681	6,722	6,730	6,736	-22	-0.3%
3400704750	Bellmawr Borough	11,429	11,359	11,359	11,359	11,359	11,398	11,438	11,443	11,446	17	0.1%
3400705440	Berlin Borough	7,571	7,536	7,719	7,925	7,925	7,951	7,979	7,989	7,992	421	5.6%
3400705470	Berlin Township	5,396	5,691	5,691	5,691	5,691	5,698	5,703	5,703	5,703	307	5.7%
3400708170	Brooklawn Borough	1,893	1,898	1,898	1,898	1,898	1,919	1,927	1,927	1,927	34	1.8%
3400710000	Camden City	75,252	73,562	73,775	74,085	74,086	74,313	74,569	74,628	74,664	-588	-0.8%
3400712280	Cherry Hill Township	70,843	71,245	71,459	75,614	75,694	75,844	76,024	76,052	76,069	5,226	7.4%
3400712550	Chesilhurst Borough	1,626	1,618	1,614	1,618	1,618	1,621	1,624	1,624	1,624	-2	-0.1%
3400713420	Clementon Borough	4,881	4,957	4,957	4,957	4,957	4,977	4,989	4,989	4,991	110	2.3%
3400714260	Collingswood Borough	13,896	13,884	13,881	13,886	13,886	13,958	14,008	14,021	14,025	129	0.9%
3400726070	Gibbsboro Borough	2,240	2,218	2,305	2,407	2,407	2,407	2,415	2,415	2,415	175	7.8%
3400726760	Gloucester Township	63,592	63,903	63,887	63,919	63,951	64,610	65,224	65,355	65,425	1,833	2.9%
3400726820	Gloucester City	11,255	11,219	11,382	11,541	11,541	11,583	11,641	11,658	11,665	410	3.6%
3400728740	Haddon Township	14,423	14,541	14,541	14,541	14,542	14,620	14,706	14,719	14,723	300	2.1%
3400728770	Haddonfield Borough	11,356	11,317	11,317	11,317	11,317	11,350	11,395	11,395	11,401	45	0.4%
3400728800	Haddon Heights Borough	7,448	7,529	7,529	7,529	7,529	7,537	7,569	7,575	7,577	129	1.7%
3400732220	Hi-Nella Borough	835	858	858	858	858	863	863	863	863	28	3.4%
3400739210	Laurel Springs Borough	1,866	1,866	1,866	1,866	1,866	1,866	1,873	1,873	1,873	7	0.4%
3400739420	Lawnside Borough	2,907	2,882	2,882	2,882	2,882	2,896	2,900	2,900	2,904	-3	-0.1%
3400740440	Lindenwold Borough	17,385	17,263	17,263	17,269	17,270	17,335	17,414	17,441	17,461	76	0.4%
3400742630	Magnolia Borough	4,299	4,273	4,273	4,273	4,273	4,278	4,286	4,287	4,293	-6	-0.1%
3400745510	Merchantville Borough	3,707	3,700	3,700	3,702	3,702	3,710	3,734	3,738	3,738	31	0.8%
3400748750	Mount Ephraim Borough	4,632	4,587	4,587	4,587	4,587	4,600	4,607	4,608	4,608	-24	-0.5%
3400753880	Oaklyn Borough	3,968	3,955	3,955	3,955	3,955	3,985	4,015	4,016	4,016	48	1.2%
3400757660	Pennsauken Township	35,552	35,761	35,899	36,055	36,060	36,159	36,286	36,299	36,307	755	2.1%
3400758770	Pine Hill Borough	10,410	10,417	10,417	10,417	10,417	10,434	10,458	10,463	10,467	57	0.5%
3400758920	Pine Valley Borough	11	11	11	11	11	11	11	11	11	0	0.0%
3400765160	Runnemede Borough	8,303	8,300	8,300	8,300	8,300	8,327	8,335	8,339	8,343	40	0.5%

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ID	Municipality or District	2015 Base	2019 Forecast	2020 Forecast	2025 Forecast	2030 Forecast	2035 Forecast	2040 Forecast	2045 Forecast	2050 Forecast	2015-2050 Absolute Change	2015-2050 Percentage Change
3400768340	Somerdale Borough	5,405	5,477	5,477	5,477	5,477	5,477	5,487	5,494	5,498	93	1.7%
3400771220	Stratford Borough	6,972	6,955	6,951	6,955	6,955	7,001	7,035	7,041	7,044	72	1.0%
3400772240	Tavistock Borough	4	6	6	6	6	6	6	6	6	2	50.0%
3400776220	Voorhees Township	29,202	29,175	29,133	29,177	29,183	29,326	29,476	29,514	29,525	323	1.1%
3400777630	Waterford Township	10,718	10,684	10,681	10,685	10,685	10,697	10,709	10,709	10,711	-7	-0.1%
3400781740	Winslow Township	39,051	38,629	38,609	38,669	38,700	39,548	40,479	40,659	40,773	1,722	4.4%
3400782450	Woodlynne Borough	2,916	2,915	2,915	2,915	2,915	2,922	2,926	2,940	2,940	24	0.8%

Source: DVRPC, 2021

Table A-3: Gloucester County Forecasted Population by Municipality, 2015–2050

ID	Municipality or District	2015 Base	2019 Forecast	2020 Forecast	2025 Forecast	2030 Forecast	2035 Forecast	2040 Forecast	2045 Forecast	2050 Forecast	2015-2050 Absolute Change	2015-2050 Percentage Change
3401513360	Clayton Borough	8,475	8,738	8,738	9,102	9,247	9,635	9,650	9,691	9,747	1,272	15.0%
3401517710	Deptford Township	30,519	30,349	30,337	30,378	30,407	31,003	31,500	31,579	31,623	1,104	3.6%
3401519180	East Greenwich Township	10,310	10,719	10,712	10,720	10,720	10,736	10,744	10,744	10,744	434	4.2%
3401521060	Elk Township	4,094	4,173	4,172	4,252	4,301	4,621	4,650	4,737	4,840	746	18.2%
3401524840	Franklin Township	16,585	16,300	16,299	16,307	16,318	16,753	17,063	17,101	17,144	559	3.4%
3401526340	Glassboro Borough	19,207	20,288	20,431	20,655	20,709	21,245	21,380	21,513	21,661	2,454	12.8%
3401528185	Greenwich Township	4,831	4,795	4,795	4,795	4,795	4,818	4,831	4,836	4,844	13	0.3%
3401530180	Harrison Township	12,897	13,116	13,116	13,537	13,632	13,758	14,209	16,096	17,912	5,015	38.9%
3401541160	Logan Township	5,981	5,874	5,874	5,907	5,955	6,409	6,437	6,446	6,451	470	7.9%
3401543440	Mantua Township	15,076	14,840	14,846	15,334	15,557	16,357	16,620	18,087	19,149	4,073	27.0%
3401547250	Monroe Township	36,796	36,865	36,858	37,577	37,834	38,562	39,200	41,973	44,595	7,799	21.2%
3401549680	National Park Borough	2,987	2,943	2,943	2,943	2,943	2,943	2,958	2,958	2,958	-29	-1.0%
3401551390	Newfield Borough	1,568	1,543	1,543	1,543	1,545	1,556	1,558	1,563	1,563	-5	-0.3%
3401557150	Paulsboro Borough	5,952	5,854	5,854	5,854	5,854	5,872	5,882	5,885	5,896	-56	-0.9%
3401559070	Pitman Borough	8,871	8,741	8,723	8,743	8,743	8,782	8,817	8,818	8,821	-50	-0.6%
3401569030	South Harrison Township	3,177	3,123	3,123	3,128	3,142	3,389	3,447	3,476	3,501	324	10.2%
3401571850	Swedesboro Borough	2,599	2,568	2,568	2,568	2,568	2,580	2,595	2,595	2,597	-2	-0.1%
3401577180	Washington Township	48,168	47,753	47,741	47,779	47,799	48,421	49,017	49,160	49,209	1,041	2.2%
3401578110	Wenonah Borough	2,258	2,212	2,212	2,212	2,212	2,215	2,238	2,238	2,238	-20	-0.9%
3401578800	West Deptford Township	21,330	20,980	20,971	21,025	21,063	22,140	23,019	23,251	23,404	2,074	9.7%
3401580120	Westville Borough	4,200	4,144	4,144	4,148	4,149	4,160	4,180	4,181	4,187	-13	-0.3%
3401582120	Woodbury City	9,954	9,794	9,789	9,795	9,796	9,831	9,849	9,859	9,862	-92	-0.9%
3401582180	Woodbury Heights Borough	2,999	2,964	2,964	2,964	2,967	2,987	3,007	3,007	3,007	8	0.3%
3401582840	Woolwich Township	12,257	12,960	12,957	13,926	16,239	18,230	19,859	21,346	21,655	9,398	76.7%

Source: DVRPC, 2021

Table A-4: Mercer County Forecasted Population by Municipality, 2015–2050

											2015-2050	
ID	Municipality or District	2015 Base	2019 Forecast	2020 Forecast	2025 Forecast	2030 Forecast	2035 Forecast	2040 Forecast	2045 Forecast	2050 Forecast	Absolute Change	Percentage Change
3402119780	East Windsor Township	27,265	27,288	27,281	27,288	28,459	28,501	28,564	28,569	28,577	1,312	4.8%
3402122185	Ewing Township	36,008	36,303	36,798	38,774	40,138	40,158	40,164	40,166	40,168	4,160	11.6%
3402129310	Hamilton Township	87,970	87,065	87,093	87,493	88,457	88,627	88,817	88,868	88,912	942	1.1%
3402131620	Hightstown Borough	5,485	5,304	5,302	5,642	6,332	6,352	6,368	6,369	6,373	888	16.2%
3402133150	Hopewell Borough	1,920	1,906	1,906	1,906	1,906	1,909	1,922	1,923	1,923	3	0.2%
3402133180	Hopewell Township	18,392	17,725	17,725	20,288	21,801	22,684	22,928	22,980	23,028	4,636	25.2%
3402139510	Lawrence Township	32,887	32,435	32,410	32,597	33,973	34,193	34,413	34,459	34,475	1,588	4.8%
3402157600	Pennington Borough	2,530	2,576	2,575	2,576	2,576	2,592	2,600	2,605	2,605	75	3.0%
3402160900	Princeton	30,157	31,187	31,168	31,346	32,048	32,214	32,336	32,360	32,374	2,217	7.4%
3402163850	Robbinsville Township	14,036	14,543	14,631	14,907	14,907	14,919	14,948	14,951	14,951	915	6.5%
3402174000	Trenton City	83,518	83,203	83,148	84,348	84,377	84,960	85,625	85,750	85,861	2,343	2.8%
3402180240	West Windsor Township	28,032	27,895	27,888	30,947	37,096	37,135	37,196	37,202	37,215	9,183	32.8%

Source: DVRPC, 2021

Table A-5: Bucks County Forecasted Population by Municipality, 2015–2050

											2015-2050	
ID	Municipality or District	2015 Base	2019 Forecast	2020 Forecast	2025 Forecast	2030 Forecast	2035 Forecast	2040 Forecast	2045 Forecast	2050 Forecast	Absolute Change	Percentage Change
4201704976	Bedminster Township	7,040	7,229	7,238	7,250	7,415	7,592	7,718	7,828	7,943	903	12.8%
4201705616	Bensalem Township	60,163	60,507	60,591	62,161	62,678	63,248	63,763	64,185	64,562	4,399	7.3%
4201708592	Bridgeton Township	1,291	1,281	1,289	1,289	1,292	1,292	1,296	1,304	1,314	23	1.8%
4201708760	Bristol Borough	9,603	9,576	9,575	9,586	9,622	9,645	9,656	9,685	9,715	112	1.2%
4201708768	Bristol Township	53,912	53,473	53,492	53,543	53,826	54,166	54,443	54,642	54,789	877	1.6%
4201709816	Buckingham Township	20,286	20,240	20,266	20,290	20,427	20,572	20,697	20,753	20,814	528	2.6%
4201712504	Chalfont Borough	4,055	4,269	4,286	4,305	4,329	4,355	4,374	4,394	4,408	353	8.7%
4201719784	Doylestown Borough	8,297	8,272	8,230	8,797	9,185	9,208	9,238	9,254	9,278	981	11.8%
4201719792	Doylestown Township	17,489	17,398	17,356	17,625	17,976	18,148	18,268	18,321	18,356	867	5.0%
4201720104	Dublin Borough	2,171	2,133	2,131	2,406	2,419	2,441	2,458	2,460	2,466	295	13.6%
4201720480	Durham Township	1,140	1,133	1,133	1,133	1,133	1,147	1,147	1,162	1,166	26	2.3%
4201721760	East Rockhill Township	5,732	5,728	5,732	5,735	5,771	5,809	5,847	5,874	5,911	179	3.1%
4201725112	Falls Township	33,599	33,520	33,529	33,539	33,602	33,633	33,662	33,711	33,724	125	0.4%
4201733224	Haycock Township	2,204	2,210	2,212	2,217	2,224	2,229	2,252	2,269	2,275	71	3.2%
4201734952	Hilltown Township	15,238	15,822	15,862	16,405	16,512	16,617	16,746	16,823	16,863	1,625	10.7%
4201736192	Hulmeville Borough	1,005	999	999	999	1,000	1,000	1,004	1,011	1,012	7	0.7%
4201737304	Ivyland Borough	942	941	930	941	946	952	963	970	977	35	3.7%
4201741392	Langhorne Borough	1,588	1,580	1,581	1,583	1,587	1,592	1,592	1,595	1,595	7	0.4%
4201741416	Langhorne Manor Borough	1,470	1,424	1,414	1,428	1,428	1,433	1,447	1,447	1,459	-11	-0.7%
4201744968	Lower Makefield Township	32,545	32,802	32,870	33,503	33,861	33,935	34,028	34,068	34,129	1,584	4.9%
4201745112	Lower Southampton Township	19,046	19,177	19,184	19,291	19,419	19,469	19,495	19,526	19,540	494	2.6%
4201749120	Middletown Township	45,201	44,966	44,923	45,007	45,280	45,617	45,923	46,238	46,456	1,255	2.8%
4201749384	Milford Township	10,010	10,056	10,065	10,087	10,239	10,372	10,551	10,698	10,820	810	8.1%
4201751144	Morrisville Borough	8,604	8,521	8,521	8,521	8,841	9,213	9,257	9,312	9,357	753	8.8%
4201753296	New Britain Borough	2,965	2,969	3,260	3,557	3,561	3,574	3,580	3,588	3,598	633	21.3%
4201753304	New Britain Township	11,241	11,524	11,531	11,542	11,739	11,913	12,033	12,126	12,213	972	8.6%
4201753712	New Hope Borough	2,505	2,530	2,533	2,534	2,541	2,560	2,565	2,568	2,579	74	3.0%
4201754184	Newtown Borough	2,241	2,240	2,244	2,247	2,267	2,292	2,296	2,312	2,316	75	3.3%
4201754192	Newtown Township	19,548	19,584	19,578	19,699	19,830	19,905	19,967	20,004	20,050	502	2.6%
4201754576	Nockamixon Township	3,416	3,376	3,378	3,379	3,400	3,406	3,427	3,441	3,448	32	0.9%

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ID	Municipality or District	2015 Base	2019 Forecast	2020 Forecast	2025 Forecast	2030 Forecast	2035 Forecast	2040 Forecast	2045 Forecast	2050 Forecast	2015-2050 Absolute Change	2015-2050 Percentage Change
4201754688	Northampton Township	39,349	39,164	39,169	39,668	39,925	40,145	40,284	40,458	40,564	1,215	3.1%
4201758936	Penndel Borough	2,186	2,157	2,157	2,157	2,160	2,188	2,201	2,216	2,228	42	1.9%
4201759384	Perkasie Borough	8,391	8,738	8,751	8,751	8,787	8,851	8,876	8,921	8,935	544	6.5%
4201761616	Plumstead Township	13,432	14,483	14,488	14,554	14,981	15,354	15,746	16,052	16,357	2,925	21.8%
4201763048	Quakertown Borough	8,729	8,661	8,750	8,853	8,898	8,926	8,971	9,002	9,044	315	3.6%
4201764536	Richland Township	13,249	13,448	13,515	13,845	14,064	14,300	14,529	14,685	14,836	1,587	12.0%
4201764584	Richlandtown Borough	1,307	1,297	1,287	1,297	1,297	1,302	1,308	1,310	1,310	3	0.2%
4201764856	Riegelsville Borough	856	852	852	852	852	852	852	852	853	-3	-0.4%
4201769248	Sellersville Borough	4,256	4,283	4,282	4,418	4,462	4,513	4,549	4,560	4,571	315	7.4%
4201770744	Silverdale Borough	853	854	854	854	855	855	856	858	862	9	1.1%
4201771752	Solebury Township	8,598	8,552	8,553	8,553	8,584	8,614	8,636	8,662	8,685	87	1.0%
4201773016	Springfield Township	5,060	5,033	5,041	5,041	5,068	5,085	5,103	5,120	5,126	66	1.3%
4201776304	Telford Borough	2,182	2,205	2,196	2,338	2,505	2,527	2,528	2,528	2,533	351	16.1%
4201776784	Tinicum Township	3,972	3,952	3,965	3,973	4,008	4,044	4,087	4,105	4,116	144	3.6%
4201777704	Trumbauersville Borough	955	935	935	935	944	944	946	946	954	-1	-0.1%
4201777744	Tullytown Borough	2,205	2,181	2,183	2,183	2,211	2,217	2,219	2,221	2,224	19	0.9%
4201779128	Upper Makefield Township	8,191	8,600	8,600	8,602	8,643	8,656	8,676	8,707	8,714	523	6.4%
4201779296	Upper Southampton Township	15,081	14,956	14,946	14,968	15,108	15,233	15,310	15,394	15,443	362	2.4%
4201780952	Warminster Township	32,632	32,348	32,414	32,457	32,743	33,137	33,416	33,639	33,792	1,160	3.6%
4201781048	Warrington Township	23,796	24,560	24,581	25,038	25,229	25,484	25,658	25,795	25,888	2,092	8.8%
4201781144	Warwick Township	14,574	14,699	14,753	14,981	15,123	15,264	15,395	15,489	15,547	973	6.7%
4201783960	West Rockhill Township	5,264	5,221	5,221	5,234	5,350	5,442	5,573	5,631	5,674	410	7.8%
4201786624	Wrightstown Township	3,101	3,097	3,100	3,103	3,114	3,130	3,154	3,163	3,173	72	2.3%
4201786920	Yardley Borough	2,459	2,514	2,514	2,514	2,525	2,532	2,547	2,559	2,569	110	4.5%

Source: DVRPC, 2021

Table A-6: Chester County Forecasted Population by Municipality, 2015–2050

ID	Municipality or District	2015 Base	2019 Forecast	2020 Forecast	2025 Forecast	2030 Forecast	2035 Forecast	2040 Forecast	2045 Forecast	2050 Forecast	2015-2050 Absolute Change	2015-2050 Percentage Change
4202903384	Atglen Borough	1,408	1,409	1,413	1,574	1,701	1,701	1,701	1,701	1,701	293	20.8%
4202903656	Avondale Borough	1,406	1,400	1,400	1,405	1,439	1,478	1,503	1,536	1,579	173	12.3%
4202906544	Birmingham Township	4,220	4,199	4,199	4,203	4,274	4,318	4,375	4,410	4,453	233	5.5%
4202910824	Caln Township	14,150	14,275	14,271	15,301	15,986	16,584	17,141	17,600	17,923	3,773	26.7%
4202912744	Charlestown Township	5,626	6,274	6,296	6,351	6,637	6,974	7,381	7,784	8,062	2,436	43.3%
4202914712	Coatesville City	13,173	13,069	13,073	13,124	13,644	14,086	14,417	14,730	14,927	1,754	13.3%
4202919752	Downingtown Borough	7,939	7,897	7,904	10,967	11,074	11,173	11,257	11,312	11,360	3,421	43.1%
4202920824	East Bradford Township	9,942	9,896	9,905	10,323	10,478	10,720	11,026	11,274	11,437	1,495	15.0%
4202920864	East Brandywine Township	8,277	9,049	9,091	10,275	10,687	11,089	11,453	11,782	11,970	3,693	44.6%
4202920920	East Caln Township	4,874	4,847	4,856	5,632	6,102	6,102	6,107	6,107	6,117	1,243	25.5%
4202921008	East Coventry Township	6,780	6,752	6,785	7,001	7,538	8,053	8,489	8,860	9,147	2,367	34.9%
4202921104	East Fallowfield Township	7,611	7,558	7,608	7,749	8,256	8,683	9,076	9,401	9,736	2,125	27.9%
4202921192	East Goshen Township	18,213	18,149	18,158	18,187	18,534	18,834	19,119	19,340	19,496	1,283	7.0%
4202921480	East Marlborough Township	7,275	7,548	7,560	8,288	8,727	9,264	9,663	10,075	10,462	3,187	43.8%
4202921576	East Nantmeal Township	1,814	1,855	1,854	1,859	1,908	1,957	2,022	2,099	2,131	317	17.5%
4202921624	East Nottingham Township	8,894	9,085	9,100	9,214	9,909	10,445	11,007	11,433	11,906	3,012	33.9%
4202921696	East Pikeland Township	7,325	7,526	7,699	8,132	8,598	9,055	9,532	9,870	10,164	2,839	38.8%
4202921928	Easttown Township	10,573	10,634	10,635	11,443	11,676	11,788	11,874	11,966	12,041	1,468	13.9%
4202922000	East Vincent Township	6,918	7,343	7,348	8,381	8,762	9,118	9,470	9,713	9,935	3,017	43.6%
4202922056	East Whiteland Township	10,613	12,832	13,204	16,055	16,524	16,599	16,671	16,743	16,808	6,195	58.4%
4202923032	Elk Township	1,696	1,708	1,708	1,719	1,794	1,885	1,943	1,995	2,057	361	21.3%
4202923440	Elverson Borough	1,308	1,308	1,316	1,381	1,453	1,550	1,668	1,764	1,830	522	39.9%
4202927376	Franklin Township	4,505	4,537	4,539	4,564	4,802	5,069	5,304	5,480	5,604	1,099	24.4%
4202934448	Highland Township	1,276	1,287	1,292	1,296	1,321	1,369	1,412	1,433	1,482	206	16.1%
4202935528	Honey Brook Borough	1,782	1,759	1,762	1,770	1,874	1,942	2,004	2,050	2,083	301	16.9%
4202935536	Honey Brook Township	8,115	8,311	8,310	8,722	9,240	9,734	10,242	10,632	11,028	2,913	35.9%
4202939344	Kennett Township	8,150	8,305	8,545	9,384	9,843	10,244	10,593	10,846	11,095	2,945	36.1%
4202939352	Kennett Square Borough	6,162	6,202	6,201	7,352	8,277	8,282	8,283	8,288	8,288	2,126	34.5%
4202944440	London Britain Township	3,227	3,240	3,241	3,246	3,278	3,341	3,379	3,409	3,442	215	6.7%
4202944456	Londonderry Township	2,401	2,552	2,555	2,571	2,666	2,774	2,889	2,989	3,066	665	27.7%

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ID	Municipality or District	2015 Base	2019 Forecast	2020 Forecast	2025 Forecast	2030 Forecast	2035 Forecast	2040 Forecast	2045 Forecast	2050 Forecast	2015-2050 Absolute Change	2015-2050 Percentage Change
4202944480	London Grove Township	8,595	8,829	8,849	9,068	9,628	10,215	10,818	11,348	11,783	3,188	37.1%
4202945040	Lower Oxford Township	5,026	5,079	5,094	5,121	5,435	5,798	6,080	6,316	6,525	1,499	29.8%
4202946792	Malvern Borough	3,417	3,455	3,457	3,466	3,607	3,791	3,951	4,053	4,165	748	21.9%
4202950232	Modena Borough	535	530	534	536	580	622	665	695	718	183	34.2%
4202953608	New Garden Township	12,131	12,206	12,218	12,447	12,832	13,276	13,779	14,146	14,534	2,403	19.8%
4202953784	Newlin Township	1,352	1,347	1,347	1,351	1,381	1,432	1,473	1,542	1,568	216	16.0%
4202953816	New London Township	5,921	5,986	5,998	6,107	6,543	6,936	7,381	7,841	8,166	2,245	37.9%
4202954936	North Coventry Township	8,010	7,959	8,011	8,098	8,660	9,171	9,601	9,952	10,277	2,267	28.3%
4202957480	Oxford Borough	5,405	5,581	5,582	5,772	5,907	6,020	6,103	6,179	6,280	875	16.2%
4202958032	Parkesburg Borough	3,695	3,993	3,995	4,276	4,584	4,647	4,705	4,750	4,807	1,112	30.1%
4202958808	Penn Township	5,511	5,515	5,547	5,680	6,349	6,931	7,466	7,974	8,339	2,828	51.3%
4202959136	Pennsbury Township	3,633	3,650	3,657	3,683	3,806	3,923	3,982	4,031	4,070	437	12.0%
4202960120	Phoenixville Borough	16,692	16,968	17,010	20,397	21,475	22,184	22,815	23,269	23,603	6,911	41.4%
4202961800	Pocopson Township	4,839	4,829	4,796	4,838	4,932	5,009	5,063	5,150	5,212	373	7.7%
4202967080	Sadsbury Township	3,878	4,110	4,128	4,520	4,910	5,373	5,826	6,159	6,386	2,508	64.7%
4202968288	Schuylkill Township	8,587	8,616	8,620	8,714	8,886	9,066	9,234	9,373	9,516	929	10.8%
4202972072	South Coatesville Borough	1,441	1,456	1,461	1,467	1,578	1,695	1,760	1,848	1,927	486	33.7%
4202972088	South Coventry Township	2,629	2,641	2,643	2,663	2,792	2,945	3,060	3,155	3,235	606	23.1%
4202972920	Spring City Borough	3,316	3,303	3,306	3,748	3,785	3,841	3,889	3,927	3,979	663	20.0%
4202976568	Thornbury Township	3,148	3,136	3,137	3,363	3,635	3,672	3,713	3,727	3,758	610	19.4%
4202977344	Tredyffrin Township	29,494	29,396	29,616	30,789	31,009	31,291	31,570	31,796	31,949	2,455	8.3%
4202979208	Upper Oxford Township	2,518	2,538	2,538	2,541	2,560	2,589	2,630	2,640	2,649	131	5.2%
4202979352	Upper Uwchlan Township	11,493	11,823	11,866	13,463	13,697	13,968	14,223	14,441	14,553	3,060	26.6%
4202979480	Uwchlan Township	18,972	18,840	18,863	19,275	20,166	20,823	21,337	21,848	22,260	3,288	17.3%
4202979544	Valley Township	7,631	7,772	7,781	8,502	8,846	9,105	9,417	9,624	9,838	2,207	28.9%
4202980616	Wallace Township	3,682	3,675	3,675	4,177	4,306	4,341	4,410	4,449	4,462	780	21.2%
4202981160	Warwick Township	2,553	2,546	2,546	2,895	2,899	2,924	2,939	2,964	2,975	422	16.5%
4202982544	West Bradford Township	12,753	13,403	13,427	13,557	13,887	14,296	14,774	15,116	15,459	2,706	21.2%
4202982576	West Brandywine Township	7,471	7,467	7,496	8,199	8,891	9,415	9,864	10,226	10,588	3,117	41.7%
4202982664	West Caln Township	9,075	9,110	9,115	9,165	9,469	9,846	10,178	10,476	10,773	1,698	18.7%

(Continued)

ID	Municipality or District	2015 Base	2019 Forecast	2020 Forecast	2025 Forecast	2030 Forecast	2035 Forecast	2040 Forecast	2045 Forecast	2050 Forecast	2015-2050 Absolute Change	2015-2050 Percentage Change
4202982704	West Chester Borough	19,929	20,029	20,131	20,833	20,970	21,151	21,291	21,402	21,557	1,628	8.2%
4202982936	West Fallowfield Township	2,600	2,590	2,592	2,596	2,636	2,691	2,739	2,777	2,794	194	7.5%
4202983080	West Goshen Township	23,059	22,973	22,993	25,055	25,487	25,854	26,139	26,386	26,592	3,533	15.3%
4202983104	West Grove Borough	2,884	2,839	2,844	2,859	2,951	3,043	3,129	3,239	3,309	425	14.7%
4202983464	West Marlborough Township	820	815	815	815	815	820	827	827	827	7	0.9%
4202983664	West Nantmeal Township	2,194	2,214	2,218	2,225	2,269	2,326	2,373	2,424	2,458	264	12.0%
4202983712	West Nottingham Township	2,716	2,709	2,710	2,721	2,777	2,854	2,895	2,939	2,991	275	10.1%
4202983832	West Pikeland Township	4,069	4,066	4,073	4,108	4,406	4,573	4,765	4,966	5,101	1,032	25.4%
4202983968	West Sadsbury Township	2,461	2,499	2,503	2,544	2,770	3,017	3,284	3,493	3,685	1,224	49.7%
4202984104	Westtown Township	10,914	11,013	11,023	11,523	12,231	12,489	12,692	12,869	13,007	2,093	19.2%
4202984160	West Vincent Township	5,029	5,911	6,514	7,170	7,511	7,888	8,170	8,346	8,507	3,478	69.2%
4202984192	West Whiteland Township	18,432	19,752	20,652	24,418	26,104	26,491	26,854	27,199	27,477	9,045	49.1%
4202985352	Willistown Township	10,880	11,014	11,009	11,254	11,336	11,454	11,526	11,615	11,684	804	7.4%

Source: DVRPC, 2021

Table A-7: Delaware County Forecasted Population by Municipality, 2015–2050

											2015-2050	
ID	Municipality or District	2015 Base	2019 Forecast	2020 Forecast	2025 Forecast	2030 Forecast	2035 Forecast	2040 Forecast	2045 Forecast	2050 Forecast	Absolute Change	Percentage Change
4204500676	Aldan Borough	4,180	4,160	4,160	4,160	4,182	4,198	4,205	4,209	4,219	39	0.9%
4204503336	Aston Township	16,714	16,745	16,741	16,754	16,798	16,868	16,917	16,948	16,970	256	1.5%
4204506024	Bethel Township	9,123	9,242	9,283	9,394	9,533	9,593	9,650	9,691	9,750	627	6.9%
4204509080	Brookhaven Borough	8,058	8,049	8,049	8,054	8,092	8,149	8,222	8,259	8,285	227	2.8%
4204512442	Chadds Ford Township	3,719	3,725	3,727	3,735	3,770	3,806	3,850	3,887	3,910	191	5.1%
4204513208	Chester City	33,992	34,000	33,965	34,027	34,128	34,317	34,481	34,616	34,705	713	2.1%
4204513212	Chester Township	4,070	4,073	4,073	4,075	4,093	4,115	4,152	4,169	4,207	137	3.4%
4204513232	Chester Heights Borough	2,604	2,742	2,747	2,747	2,768	2,783	2,792	2,799	2,819	215	8.3%
4204514264	Clifton Heights Borough	6,673	6,697	6,708	6,725	6,732	6,742	6,750	6,758	6,775	102	1.5%
4204515232	Collingdale Borough	8,805	8,794	8,794	8,800	8,838	8,880	8,919	8,960	8,976	171	1.9%
4204515432	Colwyn Borough	2,556	2,551	2,555	2,557	2,560	2,568	2,575	2,583	2,590	34	1.3%
4204515488	Concord Township	17,555	17,933	17,910	18,328	19,154	19,474	19,639	19,801	19,922	2,367	13.5%
4204518152	Darby Borough	10,694	10,702	10,660	10,702	10,725	10,753	10,777	10,814	10,835	141	1.3%
4204518160	Darby Township	9,291	9,279	9,282	9,282	9,311	9,321	9,340	9,354	9,366	75	0.8%
4204521384	East Lansdowne Borough	2,663	2,671	2,671	2,671	2,682	2,695	2,704	2,717	2,724	61	2.3%
4204522296	Eddystone Borough	2,427	2,412	2,412	2,412	2,415	2,416	2,420	2,425	2,437	10	0.4%
4204522584	Edgmont Township	4,025	4,131	4,128	4,137	4,189	4,255	4,328	4,379	4,418	393	9.8%
4204526408	Folcroft Borough	6,646	6,632	6,638	6,638	6,664	6,686	6,706	6,734	6,748	102	1.5%
4204529720	Glenolden Borough	7,126	7,164	7,164	7,164	7,180	7,204	7,221	7,237	7,255	129	1.8%
4204533144	Haverford Township	49,124	49,526	49,478	49,531	49,581	49,642	49,706	49,777	49,811	687	1.4%
4204541440	Lansdowne Borough	10,662	10,647	10,647	10,651	10,682	10,702	10,717	10,758	10,787	125	1.2%
4204544888	Lower Chichester Township	3,477	3,473	3,473	3,478	3,481	3,486	3,492	3,497	3,499	22	0.6%
4204547344	Marcus Hook Borough	2,401	2,402	2,402	2,402	2,411	2,411	2,416	2,426	2,426	25	1.0%
4204547616	Marple Township	23,639	23,955	23,888	23,955	23,979	24,003	24,025	24,034	24,051	412	1.7%
4204548480	Media Borough	5,364	5,682	5,670	5,690	5,732	5,775	5,827	5,845	5,873	509	9.5%
4204549136	Middletown Township	15,948	16,073	16,036	18,001	18,065	18,112	18,149	18,171	18,178	2,230	14.0%
4204549504	Millbourne Borough	1,146	1,160	1,160	1,160	1,160	1,175	1,177	1,183	1,194	48	4.2%
4204551176	Morton Borough	2,665	2,670	2,670	2,675	2,698	2,724	2,732	2,740	2,742	77	2.9%
4204553104	Nether Providence Township	13,771	13,780	13,762	13,783	13,824	13,863	13,924	13,943	13,958	187	1.4%
4204554224	Newtown Township	12,707	13,943	14,049	14,526	14,679	14,867	15,040	15,127	15,213	2,506	19.7%

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ID	Municipality or District	2015 Base	2019 Forecast	2020 Forecast	2025 Forecast	2030 Forecast	2035 Forecast	2040 Forecast	2045 Forecast	2050 Forecast	2015-2050 Absolute Change	2015-2050 Percentage Change
4204555664	Norwood Borough	5,899	5,897	5,897	5,902	5,910	5,938	5,957	5,973	5,995	96	1.6%
4204558176	Parkside Borough	2,314	2,330	2,330	2,330	2,335	2,339	2,347	2,352	2,354	40	1.7%
4204562792	Prospect Park Borough	6,509	6,492	6,477	6,494	6,501	6,516	6,542	6,564	6,567	58	0.9%
4204563264	Radnor Township	31,826	31,875	31,868	31,904	32,094	32,274	32,475	32,584	32,709	883	2.8%
4204564800	Ridley Township	31,072	31,204	31,205	31,222	31,378	31,518	31,634	31,740	31,820	748	2.4%
4204564832	Ridley Park Borough	7,046	7,065	7,060	7,074	7,090	7,122	7,142	7,156	7,164	118	1.7%
4204566192	Rose Valley Borough	949	948	948	948	957	963	985	989	991	42	4.4%
4204566928	Rutledge Borough	802	799	799	799	799	799	799	799	801	-1	-0.1%
4204569752	Sharon Hill Borough	5,728	5,689	5,692	5,695	5,709	5,731	5,746	5,777	5,782	54	0.9%
4204573032	Springfield Township	24,276	24,261	24,247	24,269	24,359	24,454	24,510	24,551	24,597	321	1.3%
4204575648	Swarthmore Borough	6,266	6,346	6,346	6,353	6,364	6,382	6,397	6,413	6,416	150	2.4%
4204576576	Thornbury Township	7,652	7,726	7,730	7,730	7,760	7,798	7,823	7,844	7,854	202	2.6%
4204576792	Tinicum Township	4,088	4,111	4,111	4,111	4,123	4,135	4,141	4,153	4,166	78	1.9%
4204577288	Trainer Borough	1,818	1,836	1,836	1,836	1,836	1,839	1,841	1,841	1,841	23	1.3%
4204578712	Upland Borough	3,332	3,326	3,325	3,333	3,339	3,359	3,364	3,365	3,369	37	1.1%
4204578776	Upper Chichester Township	16,887	16,959	16,963	16,967	17,034	17,132	17,233	17,263	17,312	425	2.5%
4204579000	Upper Darby Township	82,968	82,930	82,966	83,075	83,961	84,946	85,778	86,359	86,756	3,788	4.6%
4204579248	Upper Providence Township	10,383	10,444	10,444	10,450	10,492	10,537	10,579	10,626	10,660	277	2.7%
4204586968	Yeadon Borough	11,502	11,496	11,464	11,501	11,520	11,538	11,560	11,573	11,579	77	0.7%

Source: DVRPC, 2021

Table A-8: Montgomery County Forecasted Population by Municipality, 2015–2050

											2015-2050	
ID	Municipality or District	2015 Base	2019 Forecast	2020 Forecast	2025 Forecast	2030 Forecast	2035 Forecast	2040 Forecast	2045 Forecast	2050 Forecast	Absolute Change	Percentage Change
4209100156	Abington Township	55,551	55,319	55,390	56,266	56,656	57,106	57,445	57,800	58,122	2,571	4.6%
4209102264	Ambler Borough	6,493	6,491	6,482	6,508	6,667	6,765	6,870	6,948	7,021	528	8.1%
4209108568	Bridgeport Borough	4,550	4,570	4,570	4,571	6,097	6,160	6,182	6,206	6,239	1,689	37.1%
4209109696	Bryn Athyn Borough	1,396	1,404	1,403	1,407	1,417	1,437	1,451	1,456	1,463	67	4.8%
4209112968	Cheltenham Township	37,108	37,121	37,106	37,148	37,407	37,727	38,055	38,316	38,508	1,400	3.8%
4209115192	Collegeville Borough	5,257	5,174	5,193	5,204	5,288	5,359	5,414	5,485	5,529	272	5.2%
4209115848	Conshohocken Borough	7,981	8,047	8,053	10,353	10,472	10,594	10,682	10,751	10,823	2,842	35.6%
4209119672	Douglass Township	10,404	10,549	10,554	10,579	10,893	11,290	11,696	12,055	12,309	1,905	18.3%
4209121200	East Greenville Borough	2,953	2,940	2,940	2,946	2,961	2,975	3,012	3,022	3,051	98	3.3%
4209121600	East Norriton Township	14,032	13,974	14,264	14,953	15,136	15,269	15,461	15,555	15,591	1,559	11.1%
4209127280	Franconia Township	13,194	13,369	13,397	13,566	14,437	15,045	15,751	16,340	16,857	3,663	27.8%
4209131088	Green Lane Borough	511	506	506	506	508	513	513	514	517	6	1.2%
4209133088	Hatboro Borough	7,376	7,501	7,501	7,505	7,593	7,701	7,776	7,874	7,938	562	7.6%
4209133112	Hatfield Borough	3,308	3,327	3,327	3,329	3,376	3,398	3,434	3,451	3,467	159	4.8%
4209133120	Hatfield Township	17,539	17,850	17,868	17,924	18,311	18,779	19,204	19,563	19,840	2,301	13.1%
4209135808	Horsham Township	26,453	26,485	26,466	27,171	27,321	27,589	27,856	29,667	31,279	4,826	18.2%
4209138000	Jenkintown Borough	4,411	4,420	4,420	4,678	4,718	4,747	4,781	4,821	4,868	457	10.4%
4209141432	Lansdale Borough	16,523	17,083	17,070	17,662	17,755	17,905	18,062	18,149	18,235	1,712	10.4%
4209143312	Limerick Township	18,714	19,303	19,355	19,524	20,514	21,410	22,296	23,033	23,777	5,063	27.1%
4209144912	Lower Frederick Township	4,877	4,928	4,928	4,951	5,034	5,148	5,211	5,264	5,313	436	8.9%
4209144920	Lower Gwynedd Township	11,500	11,497	11,485	11,530	11,656	11,832	11,969	12,082	12,199	699	6.1%
4209144976	Lower Merion Township	58,305	60,099	60,400	63,365	63,576	64,499	64,982	65,205	65,329	7,024	12.0%
4209145008	Lower Moreland Township	13,192	13,114	13,110	13,208	13,283	13,377	13,488	13,527	13,571	379	2.9%
4209145072	Lower Pottsgrove Township	12,181	12,150	12,143	12,199	12,398	12,657	12,840	13,042	13,164	983	8.1%
4209145080	Lower Providence Township	26,141	26,873	26,880	26,980	27,422	27,742	27,942	28,110	28,267	2,126	8.1%
4209145096	Lower Salford Township	15,230	15,529	15,534	15,595	16,018	16,533	16,981	17,264	17,523	2,293	15.1%
4209147592	Marlborough Township	3,327	3,385	3,388	3,397	3,438	3,465	3,499	3,520	3,545	218	6.6%
4209150640	Montgomery Township	25,941	26,164	26,167	26,228	26,589	26,870	27,253	27,483	27,814	1,873	7.2%
4209152664	Narberth Borough	4,326	4,336	4,336	4,417	4,445	4,488	4,517	4,560	4,605	279	6.4%
4209153664	New Hanover Township	12,447	13,212	13,225	13,389	14,378	15,585	16,764	17,677	18,426	5,979	48.0%

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ID	Municipality or District	2015 Base	2019 Forecast	2020 Forecast	2025 Forecast	2030 Forecast	2035 Forecast	2040 Forecast	2045 Forecast	2050 Forecast	2015-2050 Absolute Change	2015-2050 Percentage Change
4209154656	Norristown Borough	34,539	34,341	34,334	34,403	35,020	35,653	36,227	36,726	37,128	2,589	7.5%
4209155512	North Wales Borough	3,269	3,265	3,265	3,265	3,286	3,321	3,326	3,340	3,353	84	2.6%
4209159120	Pennsburg Borough	3,860	3,855	3,848	3,859	3,893	3,920	3,950	3,979	3,997	137	3.5%
4209159392	Perkiomen Township	9,186	9,140	9,135	9,169	9,304	9,460	9,574	9,656	9,722	536	5.8%
4209161664	Plymouth Township	17,611	17,531	17,637	18,798	18,819	19,901	19,932	19,959	19,973	2,362	13.4%
4209162416	Pottstown Borough	22,620	22,600	22,604	22,649	22,961	23,254	23,548	23,785	23,961	1,341	5.9%
4209163808	Red Hill Borough	2,387	2,361	2,361	2,365	2,392	2,426	2,440	2,482	2,517	130	5.4%
4209165568	Rockledge Borough	2,556	2,530	2,530	2,534	2,540	2,545	2,572	2,575	2,586	30	1.2%
4209166576	Royersford Borough	4,785	4,755	4,755	4,759	4,850	4,952	5,069	5,179	5,251	466	9.7%
4209167528	Salford Township	2,918	2,949	2,949	2,950	3,010	3,072	3,133	3,170	3,237	319	10.9%
4209168328	Schwenksville Borough	1,389	1,379	1,382	1,387	1,404	1,435	1,465	1,475	1,505	116	8.4%
4209171016	Skippack Township	14,563	14,203	14,204	14,413	14,932	15,365	15,836	16,261	16,651	2,088	14.3%
4209171856	Souderton Borough	6,733	7,082	7,082	7,083	7,137	7,174	7,247	7,281	7,308	575	8.5%
4209173088	Springfield Township	19,502	19,848	19,803	19,868	19,954	20,064	20,157	20,224	20,288	786	4.0%
4209176304	Telford Borough	2,651	2,689	2,689	2,689	2,713	2,734	2,765	2,783	2,796	145	5.5%
4209177152	Towamencin Township	18,171	18,441	18,446	18,473	18,726	19,079	19,362	19,554	19,772	1,601	8.8%
4209177304	Trappe Borough	3,519	3,725	3,777	3,819	3,852	3,891	3,928	3,941	3,959	440	12.5%
4209179008	Upper Dublin Township	26,133	26,553	26,545	29,258	29,704	29,717	29,747	29,766	29,785	3,652	14.0%
4209179040	Upper Frederick Township	3,552	3,663	3,660	3,672	3,705	3,748	3,788	3,831	3,854	302	8.5%
4209179056	Upper Gwynedd Township	15,800	15,817	15,802	15,845	15,979	16,161	16,271	16,351	16,439	639	4.0%
4209179064	Upper Hanover Township	7,297	8,038	8,038	8,061	8,303	8,605	8,870	9,053	9,265	1,968	27.0%
4209179136	Upper Merion Township	28,522	33,027	34,161	36,359	36,801	37,258	37,565	37,803	38,017	9,495	33.3%
4209179176	Upper Moreland Township	24,188	24,031	24,715	25,404	25,628	25,858	26,119	26,293	26,448	2,260	9.3%
4209179240	Upper Pottsgrove Township	5,487	5,756	5,756	5,802	6,039	6,283	6,447	6,584	6,695	1,208	22.0%
4209179256	Upper Providence Township	23,355	24,355	24,376	24,497	26,876	27,702	28,454	28,993	29,327	5,972	25.6%
4209179280	Upper Salford Township	3,356	3,364	3,364	3,369	3,427	3,487	3,547	3,594	3,657	301	9.0%
4209182736	West Conshohocken Borough	1,383	1,432	1,432	1,432	1,454	1,467	1,494	1,498	1,512	129	9.3%
4209183696	West Norriton Township	15,698	15,613	15,629	15,680	16,099	16,565	17,020	17,305	17,576	1,878	12.0%
4209183912	West Pottsgrove Township	3,867	3,838	3,838	3,846	3,867	3,881	3,903	3,915	3,939	72	1.9%
4209184624	Whitemarsh Township	17,634	18,344	18,332	19,249	19,364	19,554	19,731	19,846	19,944	2,310	13.1%

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ID	Municipality or District	2015 Base	2019 Forecast	2020 Forecast	2025 Forecast	2030 Forecast	2035 Forecast	2040 Forecast	2045 Forecast	2050 Forecast	2015-2050 Absolute Change	2015-2050 Percentage Change
4209184888	Whitpain Township	19,079	19,240	19,568	19,929	20,126	20,341	20,531	20,653	20,770	1,691	8.9%
4209186496	Worcester Township	10,368	10,430	10,436	10,470	10,733	10,962	11,171	11,347	11,502	1,134	10.9%

Source: DVRPC, 2021

Table A-9: Philadelphia County Forecasted Population by Planning District, 2015–2050

ID	Municipality or District	2015 Base	2019 Forecast	2020 Forecast	2025 Forecast	2030 Forecast	2035 Forecast	2040 Forecast	2045 Forecast	2050 Forecast	2015-2050 Absolute Change	2015-2050 Percentage Change
4210160101	North	136,426	137,290	137,487	138,303	139,100	139,281	140,359	140,473	140,671	4,245	3.1%
4210160102	Lower Southwest	42,222	42,699	42,693	42,725	42,741	42,837	42,941	42,985	43,118	896	2.1%
4210160103	Central	125,180	134,000	138,192	154,292	166,966	170,165	170,845	171,116	172,937	47,757	38.2%
4210160104	North Delaware	95,518	98,675	98,610	98,830	98,860	99,002	99,220	99,307	99,494	3,976	4.2%
4210160105	Lower South	5,577	5,528	6,158	7,691	7,696	7,739	7,777	7,791	7,811	2,234	40.1%
4210160106	West Park	46,590	45,000	44,937	45,343	45,358	45,466	45,593	45,651	45,810	-780	-1.7%
4210160107	Lower North	90,331	94,178	95,194	100,862	103,793	104,460	104,775	104,922	105,251	14,920	16.5%
4210160108	Lower Northwest	53,325	53,629	53,721	54,101	54,265	54,377	54,559	54,605	54,786	1,461	2.7%
4210160109	River Wards	69,326	70,906	71,431	74,896	77,424	77,593	77,815	77,896	78,092	8,766	12.6%
4210160110	University - Southwest	81,183	82,986	82,994	88,761	91,707	93,568	94,021	97,023	102,295	21,112	26.0%
4210160111	West	118,116	114,347	114,249	114,687	114,824	114,965	115,209	115,302	115,567	-2,549	-2.2%
4210160112	South	137,583	135,498	135,582	136,952	137,696	137,984	138,746	138,902	139,267	1,684	1.2%
4210160113	Upper Far Northeast	68,232	68,573	68,462	68,582	68,594	68,725	68,987	69,081	69,224	992	1.5%
4210160114	Lower Northeast	107,096	107,776	107,763	107,777	107,782	107,808	107,838	107,860	107,906	810	0.8%
4210160115	Upper North	152,693	148,146	148,120	148,349	148,494	149,451	150,652	151,110	151,974	-719	-0.5%
4210160116	Lower Far Northeast	70,602	72,859	72,861	72,875	72,878	72,922	73,001	73,042	73,112	2,510	3.6%
4210160117	Upper Northwest	85,177	86,714	86,623	87,006	87,164	87,305	87,652	87,744	87,964	2,787	3.3%
4210160118	Central Northeast	86,263	85,200	85,084	85,212	85,217	85,329	85,408	85,451	85,519	-744	-0.9%

Source: DVRPC, 2021

Appendix B

Forecasted Employment by Municipality and District, 2015–2050

DELAWARE VALLEY
dvrpc
REGIONAL
PLANNING COMMISSION

Appendix B: Forecasted Employment by County and Municipality, 2015–2050

Table B-1: Burlington County Forecasted Employment by Municipality, 2015–2050

ID	Municipality or District	2015 Base	2019 Forecast	2020 Forecast	2025 Forecast	2030 Forecast	2035 Forecast	2040 Forecast	2045 Forecast	2050 Forecast	2015-2050 Absolute Change	2015-2050 Percentage Change
3400503370	Bass River Township	1,458	1,461	1,435	1,491	1,495	1,498	1,506	1,512	1,512	54	3.7%
3400505740	Beverly City	415	396	366	409	422	433	434	435	435	20	4.8%
3400506670	Bordentown City	1,457	1,505	1,387	1,487	1,526	1,550	1,583	1,608	1,627	170	11.7%
3400506700	Bordentown Township	5,153	6,576	6,174	6,368	6,379	6,381	6,402	6,422	6,471	1,318	25.6%
3400508920	Burlington City	4,493	5,009	4,612	4,693	4,712	4,738	4,784	4,860	4,927	434	9.7%
3400508950	Burlington Township	16,216	18,544	17,681	19,074	18,992	18,986	19,034	19,104	19,161	2,945	18.2%
3400512670	Chesterfield Township	1,470	1,464	1,358	1,640	1,678	1,695	1,714	1,733	1,747	277	18.8%
3400512940	Cinnaminson Township	10,061	10,954	10,103	10,373	11,081	11,038	11,004	10,960	10,911	850	8.4%
3400517080	Delanco Township	1,133	1,369	1,276	1,444	1,447	1,459	1,473	1,477	1,483	350	30.9%
3400517440	Delran Township	6,494	7,034	6,473	6,700	6,701	6,710	6,761	6,800	6,812	318	4.9%
3400518790	Eastampton Township	976	1,007	907	1,053	1,092	1,112	1,133	1,146	1,168	192	19.7%
3400520050	Edgewater Park Township	2,704	2,722	2,474	2,961	2,990	3,020	3,075	3,123	3,164	460	17.0%
3400522110	Evesham Township	24,677	25,188	23,300	24,419	24,555	24,682	24,868	25,129	25,376	699	2.8%
3400523250	Fieldsboro Borough	79	121	117	117	116	116	114	114	114	35	44.3%
3400523850	Florence Township	4,773	8,835	8,240	9,183	9,089	9,237	9,181	9,112	9,074	4,301	90.1%
3400529010	Hainesport Township	3,071	3,408	3,154	3,642	3,669	3,686	3,751	3,827	3,917	846	27.5%
3400542060	Lumberton Township	7,433	7,439	7,018	8,136	8,451	8,579	8,826	9,112	9,354	1,921	25.8%
3400543290	Mansfield Township	3,298	3,783	3,536	5,359	5,353	5,339	5,310	5,310	5,283	1,985	60.2%
3400543740	Maple Shade Township	6,459	6,677	6,046	6,554	6,612	6,668	6,742	6,790	6,837	378	5.9%
3400545120	Medford Township	11,859	11,909	10,959	11,657	11,812	11,928	12,057	12,229	12,382	523	4.4%
3400545210	Medford Lakes Borough	825	811	726	840	856	867	879	886	903	78	9.5%
3400547880	Moorestown Township	25,290	24,961	23,837	26,181	26,706	26,913	27,269	27,654	28,014	2,724	10.8%
3400548900	Mount Holly Township	8,231	8,541	8,028	8,366	8,471	8,547	8,659	8,797	8,900	669	8.1%
3400549020	Mount Laurel Township	38,643	40,718	37,537	38,305	38,458	38,560	38,809	39,174	39,471	828	2.1%
3400551510	New Hanover Township	6,892	6,757	6,644	6,615	6,646	6,697	6,745	6,776	6,792	-100	-1.5%
3400553070	North Hanover Township	1,475	1,590	1,451	1,563	1,581	1,585	1,593	1,602	1,607	132	8.9%
3400555800	Palmyra Borough	2,051	2,072	1,909	2,789	2,776	2,767	2,756	2,749	2,736	685	33.4%

(Continued)

ID	Municipality or District	2015 Base	2019 Forecast	2020 Forecast	2025 Forecast	2030 Forecast	2035 Forecast	2040 Forecast	2045 Forecast	2050 Forecast	2015-2050 Absolute Change	2015-2050 Percentage Change
3400557480	Pemberton Borough	537	542	468	513	522	530	542	542	542	5	0.9%
3400557510	Pemberton Township	9,195	9,202	8,659	9,569	9,797	9,923	10,048	10,171	10,277	1,082	11.8%
3400563510	Riverside Township	1,442	1,414	1,291	1,468	1,511	1,535	1,576	1,603	1,616	174	12.1%
3400563660	Riverton Borough	868	872	811	866	871	872	871	871	872	4	0.5%
3400566810	Shamong Township	1,690	1,690	1,549	1,682	1,726	1,756	1,783	1,819	1,842	152	9.0%
3400568610	Southampton Township	3,741	4,190	3,888	4,133	4,179	4,210	4,250	4,278	4,303	562	15.0%
3400569990	Springfield Township	1,686	1,643	1,546	1,726	1,733	1,738	1,748	1,755	1,759	73	4.3%
3400572060	Tabernacle Township	2,092	2,079	1,928	2,127	2,157	2,177	2,199	2,216	2,235	143	6.8%
3400577150	Washington Township	436	419	383	404	404	404	409	410	414	-22	-5.0%
3400578200	Westampton Township	7,796	8,140	7,443	8,667	9,941	9,974	10,088	10,181	10,250	2,454	31.5%
3400581440	Willingboro Township	8,144	8,076	7,311	8,258	8,496	8,608	8,699	8,792	8,870	726	8.9%
3400582420	Woodland Township	484	575	533	541	542	544	545	546	546	62	12.8%
3400582960	Wrightstown Borough	8,576	8,544	8,486	8,249	8,239	8,254	8,270	8,286	8,312	-264	-3.1%

Source: DVRPC, 2021

Table B-2: Camden County Forecasted Employment by Municipality, 2015–2050

											2015-2050	
ID	Municipality or District	2015 Base	2019 Forecast	2020 Forecast	2025 Forecast	2030 Forecast	2035 Forecast	2040 Forecast	2045 Forecast	2050 Forecast	Absolute Change	Percentage Change
3400702200	Audubon Borough	2,619	2,732	2,519	2,750	2,778	2,790	2,799	2,805	2,810	191	7.3%
3400702230	Audubon Park Borough	169	166	158	162	165	166	166	166	166	-3	-1.8%
3400703250	Barrington Borough	2,931	3,534	3,128	3,176	3,164	3,142	3,142	3,141	3,158	227	7.7%
3400704750	Bellmawr Borough	4,655	6,160	5,651	5,661	5,635	5,621	5,616	5,611	5,621	966	20.8%
3400705440	Berlin Borough	4,484	4,418	4,105	4,505	4,622	4,696	4,769	4,855	4,941	457	10.2%
3400705470	Berlin Township	6,015	6,271	5,861	6,041	6,090	6,102	6,134	6,185	6,238	223	3.7%
3400708170	Brooklawn Borough	677	739	635	677	674	674	679	678	678	1	0.1%
3400710000	Camden City	39,682	43,168	40,614	46,507	47,464	47,914	48,385	48,781	49,127	9,445	23.8%
3400712280	Cherry Hill Township	52,013	53,861	49,855	52,934	53,451	53,769	54,218	54,754	55,220	3,207	6.2%
3400712550	Chesilhurst Borough	229	225	211	259	274	279	288	288	288	59	25.8%
3400713420	Clementon Borough	1,348	1,327	1,201	1,345	1,369	1,397	1,438	1,465	1,485	137	10.2%
3400714260	Collingswood Borough	4,969	5,752	5,252	5,482	5,564	5,635	5,692	5,743	5,761	792	15.9%
3400726070	Gibbsboro Borough	2,078	2,035	1,915	2,065	2,085	2,103	2,121	2,140	2,154	76	3.7%
3400726760	Gloucester Township	18,405	18,360	16,953	18,412	18,786	18,980	19,257	19,577	19,819	1,414	7.7%
3400726820	Gloucester City	3,824	5,012	4,647	5,755	5,780	5,802	5,826	5,854	5,856	2,032	53.1%
3400728740	Haddon Township	4,089	4,445	4,120	4,509	4,533	4,546	4,566	4,574	4,587	498	12.2%
3400728770	Haddonfield Borough	6,618	8,513	7,935	7,880	7,861	7,866	7,873	7,881	7,886	1,268	19.2%
3400728800	Haddon Heights Borough	3,131	3,281	3,030	3,342	3,419	3,452	3,486	3,509	3,525	394	12.6%
3400732220	Hi-Nella Borough	208	445	415	412	411	410	410	410	410	202	97.1%
3400739210	Laurel Springs Borough	442	437	392	453	472	482	492	501	504	62	14.0%
3400739420	Lawnside Borough	1,734	1,793	1,681	1,807	1,809	1,813	1,818	1,828	1,835	101	5.8%
3400740440	Lindenwold Borough	2,956	3,471	3,223	3,380	3,408	3,439	3,473	3,496	3,510	554	18.7%
3400742630	Magnolia Borough	974	964	868	939	964	972	1,001	1,015	1,034	60	6.2%
3400745510	Merchantville Borough	1,291	1,307	1,217	1,374	1,401	1,410	1,417	1,424	1,433	142	11.0%
3400748750	Mount Ephraim Borough	1,137	1,137	1,028	1,199	1,232	1,233	1,240	1,253	1,267	130	11.4%
3400753880	Oaklyn Borough	935	922	866	984	1,008	1,012	1,027	1,042	1,051	116	12.4%
3400757660	Pennsauken Township	23,557	23,093	21,826	23,910	24,272	24,321	24,495	24,640	24,794	1,237	5.3%
3400758770	Pine Hill Borough	1,789	1,771	1,603	1,817	1,864	1,893	1,929	1,964	1,992	203	11.3%
3400758920	Pine Valley Borough	184	182	98	116	121	123	131	140	149	-35	-19.0%
3400765160	Runnemede Borough	2,970	3,001	2,783	3,010	3,061	3,090	3,124	3,155	3,166	196	6.6%

(Continued)

ID	Municipality or District	2015 Base	2019 Forecast	2020 Forecast	2025 Forecast	2030 Forecast	2035 Forecast	2040 Forecast	2045 Forecast	2050 Forecast	2015-2050 Absolute Change	2015-2050 Percentage Change
3400768340	Somerdale Borough	2,041	2,355	2,153	2,270	2,278	2,277	2,287	2,291	2,290	249	12.2%
3400771220	Stratford Borough	3,408	3,636	3,341	3,496	3,543	3,563	3,601	3,652	3,680	272	8.0%
3400772240	Tavistock Borough	50	49	22	42	44	46	50	52	52	2	4.0%
3400776220	Voorhees Township	18,601	18,839	17,507	18,637	18,896	19,055	19,289	19,490	19,662	1,061	5.7%
3400777630	Waterford Township	3,376	3,367	3,069	3,463	3,549	3,613	3,659	3,719	3,776	400	11.8%
3400781740	Winslow Township	11,138	12,140	11,281	12,125	12,333	12,453	12,637	12,835	12,992	1,854	16.6%
3400782450	Woodlynne Borough	328	335	312	340	350	356	358	362	367	39	11.9%

Source: DVRPC, 2021

Table B-3: Gloucester County Forecasted Employment by Municipality, 2015–2050

ID	Municipality or District	2015 Base	2019 Forecast	2020 Forecast	2025 Forecast	2030 Forecast	2035 Forecast	2040 Forecast	2045 Forecast	2050 Forecast	2015-2050 Absolute Change	2015-2050 Percentage Change
3401513360	Clayton Borough	2,180	2,414	2,269	2,621	2,728	2,798	2,892	3,010	3,086	906	41.6%
3401517710	Deptford Township	14,312	15,243	13,939	15,940	16,405	16,686	17,076	17,454	17,860	3,548	24.8%
3401519180	East Greenwich Township	2,622	3,153	2,945	3,518	3,577	3,600	3,640	3,687	3,746	1,124	42.9%
3401521060	Elk Township	1,042	1,333	1,226	1,469	1,556	1,593	1,641	1,700	1,737	695	66.7%
3401524840	Franklin Township	4,341	4,388	4,076	5,002	5,316	5,470	5,745	5,984	6,208	1,867	43.0%
3401526340	Glassboro Borough	7,414	7,355	6,604	7,632	7,987	8,207	8,495	8,823	9,129	1,715	23.1%
3401528185	Greenwich Township	2,735	2,912	2,727	2,914	2,959	2,981	3,011	3,028	3,026	291	10.6%
3401530180	Harrison Township	3,743	5,407	4,983	5,801	6,066	6,192	6,402	6,617	6,799	3,056	81.6%
3401541160	Logan Township	9,752	11,955	11,529	13,944	13,830	13,718	13,627	13,511	13,443	3,691	37.8%
3401543440	Mantua Township	5,470	5,820	5,448	6,778	7,005	7,160	7,370	7,596	7,820	2,350	43.0%
3401547250	Monroe Township	10,099	11,162	10,350	11,502	11,861	12,105	12,459	12,844	13,219	3,120	30.9%
3401549680	National Park Borough	470	463	418	498	516	525	542	563	576	106	22.6%
3401551390	Newfield Borough	467	773	724	728	725	725	725	724	722	255	54.6%
3401557150	Paulsboro Borough	1,798	2,163	2,015	2,435	2,650	2,657	2,683	2,705	2,722	924	51.4%
3401559070	Pitman Borough	2,185	2,228	2,036	2,287	2,373	2,414	2,455	2,515	2,573	388	17.8%
3401569030	South Harrison Township	864	830	780	1,044	1,119	1,149	1,185	1,221	1,255	391	45.3%
3401571850	Swedesboro Borough	1,432	1,409	1,290	1,478	1,510	1,518	1,540	1,556	1,570	138	9.6%
3401577180	Washington Township	18,675	23,343	21,310	21,625	21,663	21,756	21,937	22,118	22,306	3,631	19.4%
3401578110	Wenonah Borough	498	497	471	604	620	630	647	660	670	172	34.5%
3401578800	West Deptford Township	12,266	12,596	12,031	13,743	14,190	14,370	14,608	14,916	15,167	2,901	23.7%
3401580120	Westville Borough	1,800	1,760	1,647	1,887	2,004	2,054	2,103	2,145	2,177	377	20.9%
3401582120	Woodbury City	8,017	8,378	7,923	8,164	8,246	8,317	8,411	8,493	8,570	553	6.9%
3401582180	Woodbury Heights Borough	1,826	2,144	1,922	1,963	1,986	1,990	2,002	2,024	2,028	202	11.1%
3401582840	Woolwich Township	2,898	4,742	4,364	5,401	5,414	5,431	5,456	5,468	5,482	2,584	89.2%

Source: DVRPC, 2021

Table B-4: Mercer County Forecasted Employment by Municipality, 2015–2050

											2015-2050	
ID	Municipality or District	2015 Base	2019 Forecast	2020 Forecast	2025 Forecast	2030 Forecast	2035 Forecast	2040 Forecast	2045 Forecast	2050 Forecast	Absolute Change	Percentage Change
3402119780	East Windsor Township	11,250	12,683	11,880	12,973	13,110	13,172	13,293	13,430	13,552	2,302	20.5%
3402122185	Ewing Township	18,306	19,435	18,177	19,425	19,684	19,765	19,912	20,041	20,175	1,869	10.2%
3402129310	Hamilton Township	42,117	44,934	41,780	45,935	46,433	46,720	47,188	47,660	48,136	6,019	14.3%
3402131620	Hightstown Borough	2,511	2,601	2,462	2,620	2,659	2,679	2,718	2,761	2,793	282	11.2%
3402133150	Hopewell Borough	1,011	1,122	1,056	1,071	1,078	1,089	1,106	1,128	1,133	122	12.1%
3402133180	Hopewell Township	12,909	13,442	12,948	13,804	14,042	14,206	14,454	14,718	14,874	1,965	15.2%
3402139510	Lawrence Township	25,140	27,898	25,946	26,991	27,192	27,298	27,475	27,690	27,887	2,747	10.9%
3402157600	Pennington Borough	1,895	1,977	1,866	1,979	2,005	2,024	2,029	2,041	2,046	151	8.0%
3402160900	Princeton	21,268	21,969	20,567	22,315	22,824	23,230	23,770	24,309	24,726	3,458	16.3%
3402163850	Robbinsville Township	6,612	7,860	7,388	8,385	8,448	8,473	8,522	8,605	8,662	2,050	31.0%
3402174000	Trenton City	53,194	56,612	54,082	55,658	55,906	56,178	56,511	56,841	57,097	3,903	7.3%
3402180240	West Windsor Township	33,288	34,103	32,374	35,719	36,253	36,596	37,144	37,749	38,321	5,033	15.1%

Source: DVRPC, 2021

Table B-5: Bucks County Forecasted Employment by Municipality, 2015–2050

ID	Municipality or District	2015 Base	2019 Forecast	2020 Forecast	2025 Forecast	2030 Forecast	2035 Forecast	2040 Forecast	2045 Forecast	2050 Forecast	2015-2050 Absolute Change	2015-2050 Percentage Change
4201704976	Bedminster Township	2,036	2,159	1,976	2,272	2,301	2,332	2,379	2,423	2,466	430	21.1%
4201705616	Bensalem Township	41,286	41,655	37,840	40,022	40,361	40,501	40,649	40,873	41,172	-114	-0.3%
4201708592	Bridgeton Township	423	472	437	465	477	481	485	503	512	89	21.0%
4201708760	Bristol Borough	5,494	5,974	5,469	5,676	5,677	5,668	5,679	5,690	5,699	205	3.7%
4201708768	Bristol Township	21,524	22,155	20,341	21,524	21,681	21,704	21,806	21,925	22,009	485	2.3%
4201709816	Buckingham Township	7,948	8,342	7,682	8,167	8,355	8,446	8,574	8,715	8,816	868	10.9%
4201712504	Chalfont Borough	1,322	1,444	1,354	1,633	1,647	1,652	1,661	1,677	1,683	361	27.3%
4201719784	Doylestown Borough	10,402	10,502	9,728	10,004	10,140	10,224	10,370	10,550	10,666	264	2.5%
4201719792	Doylestown Township	12,043	12,594	11,892	12,407	12,601	12,693	12,830	12,967	13,087	1,044	8.7%
4201720104	Dublin Borough	735	719	659	1,032	1,058	1,076	1,104	1,131	1,161	426	58.0%
4201720480	Durham Township	270	297	261	273	279	284	291	289	291	21	7.8%
4201721760	East Rockhill Township	2,062	2,680	2,469	2,599	2,623	2,630	2,649	2,666	2,681	619	30.0%
4201725112	Falls Township	15,021	16,325	14,937	16,258	18,995	19,857	19,875	19,836	19,782	4,761	31.7%
4201733224	Haycock Township	547	579	539	621	641	646	650	650	650	103	18.8%
4201734952	Hilltown Township	6,062	6,556	5,953	6,537	6,641	6,695	6,791	6,931	7,038	976	16.1%
4201736192	Hulmeville Borough	229	248	231	256	261	261	261	263	266	37	16.2%
4201737304	Ivyland Borough	1,129	1,104	1,047	1,092	1,092	1,094	1,091	1,100	1,109	-20	-1.8%
4201741392	Langhorne Borough	1,072	1,572	1,398	1,394	1,388	1,391	1,393	1,390	1,389	317	29.6%
4201741416	Langhorne Manor Borough	504	504	479	578	604	608	615	625	633	129	25.6%
4201744968	Lower Makefield Township	11,892	13,772	12,959	13,158	13,156	13,164	13,182	13,193	13,224	1,332	11.2%
4201745112	Lower Southampton Township	13,033	16,053	14,738	14,511	14,397	14,338	14,284	14,246	14,199	1,166	8.9%
4201749120	Middletown Township	23,802	24,229	22,361	23,770	23,921	24,047	24,187	24,352	24,487	685	2.9%
4201749384	Milford Township	3,632	3,745	3,454	4,114	4,250	4,331	4,428	4,495	4,556	924	25.4%
4201751144	Morrisville Borough	3,085	3,031	2,788	3,072	3,165	3,220	3,268	3,312	3,369	284	9.2%
4201753296	New Britain Borough	2,606	2,638	2,523	2,639	2,697	2,716	2,731	2,765	2,780	174	6.7%
4201753304	New Britain Township	5,729	5,723	5,302	6,102	6,151	6,208	6,264	6,309	6,335	606	10.6%
4201753712	New Hope Borough	2,888	3,444	3,076	3,078	3,071	3,070	3,091	3,115	3,137	249	8.6%
4201754184	Newtown Borough	2,643	2,998	2,708	2,737	2,747	2,749	2,779	2,807	2,816	173	6.5%
4201754192	Newtown Township	14,332	15,241	14,301	14,690	14,739	14,759	14,826	14,915	14,985	653	4.6%
4201754576	Nockamixon Township	1,543	1,498	1,416	1,571	1,621	1,651	1,703	1,760	1,819	276	17.9%

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ID	Municipality or District	2015 Base	2019 Forecast	2020 Forecast	2025 Forecast	2030 Forecast	2035 Forecast	2040 Forecast	2045 Forecast	2050 Forecast	2015-2050 Absolute Change	2015-2050 Percentage Change
4201754688	Northampton Township	14,917	15,476	14,357	14,907	15,009	15,027	15,109	15,215	15,290	373	2.5%
4201758936	Penndel Borough	1,144	1,121	1,007	1,184	1,231	1,266	1,310	1,336	1,364	220	19.2%
4201759384	Perkasie Borough	2,424	2,396	2,183	2,472	2,524	2,559	2,617	2,673	2,701	277	11.4%
4201761616	Plumstead Township	6,281	6,695	6,160	6,402	6,470	6,513	6,585	6,714	6,817	536	8.5%
4201763048	Quakertown Borough	5,021	5,038	4,630	4,836	4,867	4,909	4,948	5,002	5,037	16	0.3%
4201764536	Richland Township	6,444	7,402	6,779	7,370	7,508	7,594	7,782	7,964	8,095	1,651	25.6%
4201764584	Richlandtown Borough	275	331	317	340	347	351	357	371	374	99	36.0%
4201764856	Riegelsville Borough	161	229	214	219	221	220	222	222	221	60	37.3%
4201769248	Sellersville Borough	1,155	1,354	1,218	1,306	1,347	1,373	1,407	1,433	1,467	312	27.0%
4201770744	Silverdale Borough	277	334	305	309	314	317	319	320	320	43	15.5%
4201771752	Solebury Township	3,714	3,719	3,440	3,779	3,875	3,974	4,041	4,100	4,149	435	11.7%
4201773016	Springfield Township	1,238	1,406	1,272	1,365	1,370	1,381	1,396	1,408	1,408	170	13.7%
4201776304	Telford Borough	1,024	1,088	998	1,128	1,159	1,168	1,177	1,190	1,182	158	15.4%
4201776784	Tinicum Township	1,491	1,531	1,417	1,633	1,702	1,743	1,772	1,809	1,819	328	22.0%
4201777704	Trumbauersville Borough	357	376	323	358	363	375	388	404	413	56	15.7%
4201777744	Tullytown Borough	2,268	2,221	2,060	2,163	2,206	2,237	2,298	2,358	2,400	132	5.8%
4201779128	Upper Makefield Township	2,785	2,941	2,735	2,915	2,965	2,999	3,040	3,077	3,104	319	11.5%
4201779296	Upper Southampton Township	9,613	9,469	8,773	9,243	9,360	9,450	9,582	9,684	9,769	156	1.6%
4201780952	Warminster Township	15,481	15,928	14,761	15,982	16,143	16,238	16,399	16,564	16,714	1,233	8.0%
4201781048	Warrington Township	10,121	11,771	10,745	11,069	11,182	11,261	11,402	11,561	11,727	1,606	15.9%
4201781144	Warwick Township	6,232	7,394	6,838	7,110	7,165	7,186	7,211	7,252	7,281	1,049	16.8%
4201783960	West Rockhill Township	4,891	4,777	4,526	4,950	5,166	5,261	5,407	5,561	5,687	796	16.3%
4201786624	Wrightstown Township	1,348	1,428	1,337	1,439	1,459	1,479	1,500	1,515	1,532	184	13.6%
4201786920	Yardley Borough	1,709	2,163	2,000	1,969	1,949	1,947	1,943	1,943	1,944	235	13.8%

Source: DVRPC, 2021

Table B-6: Chester County Forecasted Employment by Municipality, 2015–2050

											2015-2050	
ID	Municipality or District	2015 Base	2019 Forecast	2020 Forecast	2025 Forecast	2030 Forecast	2035 Forecast	2040 Forecast	2045 Forecast	2050 Forecast	Absolute Change	Percentage Change
4202903384	Atglen Borough	678	669	569	637	662	672	681	698	710	32	4.7%
4202903656	Avondale Borough	590	645	588	681	697	709	722	738	756	166	28.1%
4202906544	Birmingham Township	1,629	1,962	1,762	1,924	1,974	2,007	2,036	2,061	2,081	452	27.7%
4202910824	Caln Township	8,513	8,889	8,198	9,095	9,414	9,602	9,948	10,280	10,651	2,138	25.1%
4202912744	Charlestown Township	2,970	3,461	3,247	3,500	3,561	3,600	3,640	3,672	3,703	733	24.7%
4202914712	Coatesville City	1,994	2,016	1,820	2,330	2,430	2,487	2,551	2,627	2,683	689	34.6%
4202919752	Downingtown Borough	6,147	6,027	5,578	6,113	6,299	6,408	6,572	6,738	6,896	749	12.2%
4202920824	East Bradford Township	2,341	2,591	2,404	2,720	2,836	2,914	3,031	3,193	3,327	986	42.1%
4202920864	East Brandywine Township	1,693	1,671	1,546	1,967	2,123	2,197	2,291	2,409	2,514	821	48.5%
4202920920	East Caln Township	4,154	4,855	4,303	4,723	4,810	4,883	5,013	5,154	5,274	1,120	27.0%
4202921008	East Coventry Township	1,493	1,718	1,596	1,852	1,903	1,942	2,005	2,048	2,075	582	39.0%
4202921104	East Fallowfield Township	982	1,054	967	1,136	1,198	1,231	1,283	1,342	1,364	382	38.9%
4202921192	East Goshen Township	8,487	8,600	7,837	8,658	8,857	8,984	9,142	9,334	9,520	1,033	12.2%
4202921480	East Marlborough Township	5,254	5,780	5,212	6,026	6,317	6,511	6,732	6,993	7,233	1,979	37.7%
4202921576	East Nantmeal Township	800	837	701	906	936	947	953	953	953	153	19.1%
4202921624	East Nottingham Township	1,679	3,058	2,781	2,799	2,794	2,804	2,811	2,819	2,825	1,146	68.3%
4202921696	East Pikeland Township	3,077	3,240	2,924	3,449	3,629	3,732	3,864	4,012	4,151	1,074	34.9%
4202921928	Easttown Township	5,949	6,278	5,811	6,204	6,347	6,463	6,576	6,713	6,838	889	14.9%
4202922000	East Vincent Township	1,826	2,007	1,840	2,280	2,425	2,504	2,604	2,727	2,797	971	53.2%
4202922056	East Whiteland Township	25,736	27,393	25,254	30,485	31,136	31,444	31,964	32,665	33,256	7,520	29.2%
4202923032	Elk Township	404	737	673	693	703	707	714	723	730	326	80.7%
4202923440	Elverson Borough	576	743	701	764	791	811	812	817	817	241	41.8%
4202927376	Franklin Township	736	839	773	965	1,012	1,037	1,076	1,097	1,113	377	51.2%
4202934448	Highland Township	511	600	575	645	665	671	673	673	673	162	31.7%
4202935528	Honey Brook Borough	414	413	368	451	473	489	505	507	513	99	23.9%
4202935536	Honey Brook Township	3,092	3,365	3,153	3,633	3,764	3,844	3,956	4,124	4,294	1,202	38.9%
4202939344	Kennett Township	6,028	6,824	6,278	6,739	6,905	7,002	7,150	7,306	7,432	1,404	23.3%
4202939352	Kennett Square Borough	3,698	3,632	3,314	3,677	3,828	3,952	4,120	4,272	4,408	710	19.2%
4202944440	London Britain Township	643	702	630	699	730	747	768	787	804	161	25.0%
4202944456	Londonderry Township	437	487	459	542	562	571	589	598	622	185	42.3%

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ID	Municipality or District	2015 Base	2019 Forecast	2020 Forecast	2025 Forecast	2030 Forecast	2035 Forecast	2040 Forecast	2045 Forecast	2050 Forecast	2015-2050 Absolute Change	2015-2050 Percentage Change
4202944480	London Grove Township	2,815	3,167	2,933	3,558	3,663	3,732	3,845	3,949	4,018	1,203	42.7%
4202945040	Lower Oxford Township	1,877	1,845	1,723	2,448	2,653	2,740	2,864	3,000	3,088	1,211	64.5%
4202946792	Malvern Borough	2,430	2,487	2,264	2,647	2,725	2,776	2,845	2,891	2,954	524	21.6%
4202950232	Modena Borough	129	127	117	129	137	141	144	148	151	22	17.1%
4202953608	New Garden Township	6,242	6,434	5,942	6,718	6,974	7,113	7,326	7,498	7,674	1,432	22.9%
4202953784	Newlin Township	283	383	354	392	404	408	426	428	428	145	51.2%
4202953816	New London Township	1,033	1,014	925	1,144	1,214	1,247	1,308	1,368	1,396	363	35.1%
4202954936	North Coventry Township	3,037	3,480	3,102	3,299	3,351	3,407	3,475	3,562	3,644	607	20.0%
4202957480	Oxford Borough	2,183	2,139	1,996	2,378	2,527	2,604	2,728	2,847	2,926	743	34.0%
4202958032	Parkesburg Borough	727	728	667	841	888	907	951	1,007	1,044	317	43.6%
4202958808	Penn Township	2,551	2,766	2,582	2,931	3,035	3,121	3,237	3,372	3,464	913	35.8%
4202959136	Pennsbury Township	1,284	1,347	1,245	1,381	1,452	1,490	1,536	1,570	1,615	331	25.8%
4202960120	Phoenixville Borough	6,581	6,594	5,980	6,802	7,203	7,437	7,703	7,941	8,066	1,485	22.6%
4202961800	Pocopson Township	1,007	1,036	993	1,116	1,162	1,190	1,234	1,286	1,323	316	31.4%
4202967080	Sadsbury Township	1,961	1,917	1,724	2,394	2,491	2,539	2,608	2,680	2,745	784	40.0%
4202968288	Schuylkill Township	4,050	3,993	3,740	4,239	4,372	4,430	4,511	4,608	4,699	649	16.0%
4202972072	South Coatesville Borough	1,348	1,310	1,248	1,321	1,291	1,264	1,251	1,242	1,226	-122	-9.1%
4202972088	South Coventry Township	1,196	1,294	1,189	1,289	1,313	1,331	1,361	1,385	1,405	209	17.5%
4202972920	Spring City Borough	966	1,046	943	1,020	1,035	1,035	1,046	1,059	1,078	112	11.6%
4202976568	Thornbury Township	1,194	1,271	1,154	1,358	1,433	1,471	1,525	1,612	1,663	469	39.3%
4202977344	Tredyffrin Township	51,533	54,442	51,605	54,649	55,341	55,913	56,615	57,306	57,945	6,412	12.4%
4202979208	Upper Oxford Township	488	496	459	573	611	635	642	647	654	166	34.0%
4202979352	Upper Uwchlan Township	4,249	4,690	4,360	5,031	5,226	5,309	5,424	5,595	5,717	1,468	34.5%
4202979480	Uwchlan Township	14,270	15,942	14,575	15,720	16,070	17,328	17,672	18,026	18,367	4,097	28.7%
4202979544	Valley Township	2,173	2,218	2,034	2,751	2,874	2,916	2,982	3,093	3,168	995	45.8%
4202980616	Wallace Township	951	1,113	1,012	1,121	1,157	1,166	1,177	1,183	1,190	239	25.1%
4202981160	Warwick Township	726	789	718	811	838	849	865	881	895	169	23.3%
4202982544	West Bradford Township	2,201	2,648	2,400	2,562	2,638	2,678	2,737	2,795	2,828	627	28.5%
4202982576	West Brandywine Township	2,047	2,092	1,926	2,349	2,499	2,600	2,766	2,911	3,065	1,018	49.7%
4202982664	West Caln Township	1,492	1,705	1,561	1,654	1,678	1,698	1,731	1,764	1,779	287	19.2%

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ID	Municipality or District	2015 Base	2019 Forecast	2020 Forecast	2025 Forecast	2030 Forecast	2035 Forecast	2040 Forecast	2045 Forecast	2050 Forecast	2015-2050 Absolute Change	2015-2050 Percentage Change
4202982704	West Chester Borough	9,844	10,654	9,837	10,290	10,451	10,576	10,766	10,926	11,111	1,267	12.9%
4202982936	West Fallowfield Township	925	983	927	1,091	1,159	1,190	1,232	1,267	1,275	350	37.8%
4202983080	West Goshen Township	24,970	25,702	23,616	26,505	27,063	27,443	27,962	28,563	29,129	4,159	16.7%
4202983104	West Grove Borough	695	731	668	771	817	845	892	930	954	259	37.3%
4202983464	West Marlborough Township	306	299	275	377	384	386	387	392	397	91	29.7%
4202983664	West Nantmeal Township	666	656	593	754	808	837	862	881	899	233	35.0%
4202983712	West Nottingham Township	1,792	2,055	1,932	2,109	2,176	2,215	2,275	2,320	2,345	553	30.9%
4202983832	West Pikeland Township	949	1,073	994	1,139	1,194	1,223	1,245	1,277	1,294	345	36.4%
4202983968	West Sadsbury Township	1,932	2,360	2,093	2,316	2,408	2,432	2,532	2,635	2,735	803	41.6%
4202984104	Westtown Township	4,170	5,205	4,851	5,003	5,067	5,105	5,163	5,237	5,300	1,130	27.1%
4202984160	West Vincent Township	1,551	1,583	1,444	1,809	1,889	1,941	2,026	2,097	2,156	605	39.0%
4202984192	West Whiteland Township	21,517	22,126	20,359	25,117	25,269	25,382	25,609	25,829	26,143	4,626	21.5%
4202985352	Willistown Township	7,784	7,865	7,383	8,121	8,362	8,481	8,569	8,636	8,698	914	11.7%

Source: DVRPC, 2021

Table B-7: Delaware County Forecasted Employment by Municipality, 2015–2050

ID	Municipality or District	2015 Base	2019 Forecast	2020 Forecast	2025 Forecast	2030 Forecast	2035 Forecast	2040 Forecast	2045 Forecast	2050 Forecast	2015-2050 Absolute Change	2015-2050 Percentage Change
4204500676	Aldan Borough	870	887	863	907	924	939	956	974	986	116	13.3%
4204503336	Aston Township	6,342	7,122	6,728	7,197	7,203	7,204	7,257	7,290	7,317	975	15.4%
4204506024	Bethel Township	2,307	2,688	2,529	2,687	2,690	2,683	2,681	2,679	2,675	368	16.0%
4204509080	Brookhaven Borough	2,386	2,728	2,564	2,586	2,585	2,595	2,618	2,645	2,670	284	11.9%
4204512442	Chadds Ford Township	4,072	4,558	4,312	4,773	4,826	4,877	4,961	5,061	5,153	1,081	26.5%
4204513208	Chester City	12,377	12,346	11,592	13,100	13,474	13,654	13,888	14,068	14,178	1,801	14.6%
4204513212	Chester Township	3,012	3,736	3,613	3,651	3,639	3,627	3,638	3,684	3,692	680	22.6%
4204513232	Chester Heights Borough	885	1,206	1,119	1,111	1,108	1,104	1,102	1,101	1,099	214	24.2%
4204514264	Clifton Heights Borough	2,207	2,547	2,403	2,456	2,468	2,483	2,503	2,533	2,569	362	16.4%
4204515232	Collingdale Borough	2,089	2,572	2,406	2,429	2,446	2,450	2,457	2,473	2,475	386	18.5%
4204515432	Colwyn Borough	414	411	388	429	446	451	454	462	469	55	13.3%
4204515488	Concord Township	11,479	12,982	12,354	13,309	13,385	13,432	13,526	13,640	13,739	2,260	19.7%
4204518152	Darby Borough	4,016	3,983	3,733	3,890	3,955	4,008	4,067	4,131	4,189	173	4.3%
4204518160	Darby Township	2,330	3,074	2,921	2,896	2,882	2,874	2,880	2,897	2,906	576	24.7%
4204521384	East Lansdowne Borough	634	629	602	630	643	657	684	705	717	83	13.1%
4204522296	Eddystone Borough	2,983	2,948	2,862	3,413	3,437	3,445	3,462	3,486	3,504	521	17.5%
4204522584	Edgmont Township	2,120	2,492	2,291	2,479	2,515	2,552	2,587	2,611	2,631	511	24.1%
4204526408	Folcroft Borough	2,921	2,934	2,819	2,906	2,933	2,939	2,969	3,014	3,051	130	4.5%
4204529720	Glenolden Borough	2,362	2,662	2,494	2,569	2,588	2,587	2,608	2,602	2,624	262	11.1%
4204533144	Haverford Township	16,456	17,975	16,641	17,400	17,616	17,719	17,879	18,083	18,227	1,771	10.8%
4204541440	Lansdowne Borough	2,549	2,674	2,536	2,655	2,719	2,753	2,786	2,810	2,836	287	11.3%
4204544888	Lower Chichester Township	1,226	1,301	1,273	1,339	1,355	1,363	1,378	1,397	1,412	186	15.2%
4204547344	Marcus Hook Borough	2,393	2,331	2,300	2,395	2,447	2,460	2,491	2,544	2,607	214	8.9%
4204547616	Marple Township	13,968	14,125	13,308	13,984	14,176	14,310	14,431	14,575	14,709	741	5.3%
4204548480	Media Borough	11,941	12,550	12,165	12,564	12,779	12,923	13,111	13,305	13,452	1,511	12.7%
4204549136	Middletown Township	11,874	12,042	11,445	13,873	13,992	14,076	14,173	14,284	14,358	2,484	20.9%
4204549504	Millbourne Borough	306	310	280	327	329	333	337	340	338	32	10.5%
4204551176	Morton Borough	1,309	1,295	1,251	1,379	1,417	1,432	1,445	1,453	1,458	149	11.4%
4204553104	Nether Providence Township	4,404	4,420	4,171	4,625	4,726	4,794	4,861	4,892	4,902	498	11.3%
4204554224	Newtown Township	12,347	13,848	12,948	13,699	13,734	13,772	13,823	13,893	13,955	1,608	13.0%

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ID	Municipality or District	2015 Base	2019 Forecast	2020 Forecast	2025 Forecast	2030 Forecast	2035 Forecast	2040 Forecast	2045 Forecast	2050 Forecast	2015-2050 Absolute Change	2015-2050 Percentage Change
4204555664	Norwood Borough	1,103	2,049	1,939	1,908	1,901	1,899	1,897	1,896	1,895	792	71.8%
4204558176	Parkside Borough	266	264	254	290	299	305	307	312	312	46	17.3%
4204562792	Prospect Park Borough	1,838	2,532	2,367	2,366	2,355	2,352	2,357	2,356	2,360	522	28.4%
4204563264	Radnor Township	25,395	25,827	24,561	26,069	26,366	26,586	26,875	27,156	27,382	1,987	7.8%
4204564800	Ridley Township	12,643	12,664	11,908	12,723	12,880	12,963	13,080	13,182	13,285	642	5.1%
4204564832	Ridley Park Borough	2,736	2,766	2,631	2,837	2,884	2,921	2,956	2,990	3,017	281	10.3%
4204566192	Rose Valley Borough	278	514	482	479	477	476	474	473	472	194	69.8%
4204566928	Rutledge Borough	119	154	144	147	150	150	150	150	150	31	26.1%
4204569752	Sharon Hill Borough	2,962	2,931	2,819	2,945	2,967	2,985	3,033	3,100	3,148	186	6.3%
4204573032	Springfield Township	14,184	14,724	13,846	14,337	14,497	14,623	14,777	14,907	15,009	825	5.8%
4204575648	Swarthmore Borough	2,329	2,393	2,274	2,459	2,501	2,527	2,564	2,579	2,592	263	11.3%
4204576576	Thornbury Township	2,235	2,255	2,124	2,479	2,566	2,598	2,654	2,703	2,723	488	21.8%
4204576792	Tinicum Township	10,558	10,824	10,563	10,891	11,407	11,428	11,465	11,493	11,537	979	9.3%
4204577288	Trainer Borough	2,180	2,108	2,074	2,162	2,191	2,208	2,226	2,238	2,247	67	3.1%
4204578712	Upland Borough	905	940	901	937	959	969	984	1,007	1,015	110	12.2%
4204578776	Upper Chichester Township	6,788	7,608	7,243	7,437	7,459	7,459	7,501	7,530	7,568	780	11.5%
4204579000	Upper Darby Township	23,122	24,319	22,942	24,201	24,504	24,758	25,142	25,534	25,925	2,803	12.1%
4204579248	Upper Providence Township	4,580	4,576	4,348	4,806	4,936	5,022	5,127	5,218	5,260	680	14.8%
4204586968	Yeadon Borough	2,617	2,649	2,520	2,641	2,662	2,682	2,698	2,719	2,731	114	4.4%

Source: DVRPC, 2021

Table B-8: Montgomery County Forecasted Employment by Municipality, 2015–2050

ID	Municipality or District	2015 Base	2019 Forecast	2020 Forecast	2025 Forecast	2030 Forecast	2035 Forecast	2040 Forecast	2045 Forecast	2050 Forecast	2015-2050 Absolute Change	2015-2050 Percentage Change
4209100156	Abington Township	33,618	35,725	32,974	34,416	34,562	34,641	34,812	35,011	35,174	1,556	4.6%
4209102264	Ambler Borough	2,974	3,074	2,781	2,937	3,004	3,044	3,107	3,181	3,241	267	9.0%
4209108568	Bridgeport Borough	2,078	2,184	1,987	2,151	2,180	2,193	2,217	2,247	2,259	181	8.7%
4209109696	Bryn Athyn Borough	1,302	1,414	1,304	1,403	1,428	1,441	1,451	1,465	1,482	180	13.8%
4209112968	Cheltenham Township	17,700	18,727	17,369	18,202	18,365	18,523	18,724	18,886	19,053	1,353	7.6%
4209115192	Collegeville Borough	2,805	2,826	2,524	2,822	2,879	2,920	2,953	2,992	3,022	217	7.7%
4209115848	Conshohocken Borough	7,541	7,878	7,275	10,402	10,695	10,846	11,004	11,157	11,282	3,741	49.6%
4209119672	Douglass Township	3,627	3,993	3,583	4,410	4,492	4,540	4,593	4,665	4,738	1,111	30.6%
4209121200	East Greenville Borough	639	664	599	648	672	699	708	728	727	88	13.8%
4209121600	East Norriton Township	10,589	11,321	10,384	11,207	11,432	11,565	11,762	11,945	12,099	1,510	14.3%
4209127280	Franconia Township	7,120	7,685	7,131	7,405	7,517	7,569	7,704	7,875	8,057	937	13.2%
4209131088	Green Lane Borough	192	197	177	202	211	213	215	214	216	24	12.5%
4209133088	Hatboro Borough	4,853	4,794	4,328	4,623	4,677	4,748	4,826	4,895	4,924	71	1.5%
4209133112	Hatfield Borough	1,388	1,498	1,367	1,432	1,453	1,457	1,483	1,520	1,557	169	12.2%
4209133120	Hatfield Township	17,530	18,540	17,124	18,578	18,820	18,931	19,257	19,730	20,061	2,531	14.4%
4209135808	Horsham Township	31,325	32,346	30,418	31,912	32,371	32,670	33,069	34,393	35,779	4,454	14.2%
4209138000	Jenkintown Borough	4,499	4,800	4,469	4,465	4,477	4,497	4,524	4,576	4,646	147	3.3%
4209141432	Lansdale Borough	8,052	8,075	7,404	8,193	8,420	8,574	8,732	8,896	9,025	973	12.1%
4209143312	Limerick Township	12,339	13,067	11,742	13,169	13,611	13,889	14,331	14,767	15,172	2,833	23.0%
4209144912	Lower Frederick Township	986	1,057	952	1,029	1,047	1,059	1,088	1,127	1,159	173	17.5%
4209144920	Lower Gwynedd Township	6,944	7,343	6,814	7,520	7,789	7,956	8,135	8,339	8,525	1,581	22.8%
4209144976	Lower Merion Township	54,209	58,937	55,080	57,398	57,663	58,446	60,021	60,401	60,625	6,416	11.8%
4209145008	Lower Moreland Township	8,100	8,519	7,861	8,491	8,620	8,711	8,827	8,963	9,072	972	12.0%
4209145072	Lower Pottsgrove Township	4,825	4,922	4,528	5,096	5,282	5,386	5,518	5,686	5,841	1,016	21.1%
4209145080	Lower Providence Township	12,218	13,146	12,029	12,415	12,513	12,553	12,668	12,808	12,902	684	5.6%
4209145096	Lower Salford Township	8,255	8,667	8,087	8,734	8,954	9,090	9,236	9,379	9,488	1,233	14.9%
4209147592	Marlborough Township	1,069	1,161	1,015	1,112	1,142	1,159	1,187	1,214	1,232	163	15.2%
4209150640	Montgomery Township	17,242	19,357	17,452	18,561	18,667	18,748	18,922	19,200	19,413	2,171	12.6%
4209152664	Narberth Borough	2,337	2,507	2,333	2,485	2,545	2,573	2,605	2,640	2,652	315	13.5%
4209153664	New Hanover Township	12,447	13,212	13,225	13,389	14,378	15,585	16,764	17,677	18,426	5,979	48.0%

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											2015-2050	
ID	Municipality or District	2015 NETS	2019 Forecast	2020 Forecast	2025 Forecast	2030 Forecast	2035 Forecast	2040 Forecast	2045 Forecast	2050 Forecast	Absolute Change	Percentage Change
4209154656	Norristown Borough	13,296	13,391	12,520	13,556	13,919	14,151	14,438	14,718	14,947	1,651	12.4%
4209155512	North Wales Borough	1,425	1,598	1,463	1,548	1,570	1,585	1,607	1,621	1,620	195	13.7%
4209159120	Pennsburg Borough	1,448	1,562	1,409	1,494	1,521	1,538	1,565	1,597	1,637	189	13.1%
4209159392	Perkiomen Township	2,398	2,929	2,704	2,760	2,762	2,758	2,759	2,767	2,784	386	16.1%
4209161664	Plymouth Township	22,655	23,822	21,928	25,011	25,463	25,785	26,272	26,740	27,116	4,461	19.7%
4209162416	Pottstown Borough	10,222	10,525	9,639	10,657	11,054	11,327	11,735	12,137	12,485	2,263	22.1%
4209163808	Red Hill Borough	627	638	575	663	686	707	720	746	772	145	23.1%
4209165568	Rockledge Borough	1,125	1,146	1,063	1,183	1,216	1,237	1,264	1,306	1,332	207	18.4%
4209166576	Royersford Borough	1,519	1,753	1,614	1,708	1,738	1,745	1,768	1,801	1,821	302	19.9%
4209167528	Salford Township	597	725	646	717	727	740	748	753	753	156	26.1%
4209168328	Schwenksville Borough	463	485	436	494	514	521	539	559	568	105	22.7%
4209171016	Skippack Township	4,263	4,467	4,162	4,395	4,453	4,495	4,545	4,618	4,683	420	9.9%
4209171856	Souderton Borough	2,686	2,817	2,584	2,980	3,054	3,103	3,147	3,199	3,223	537	20.0%
4209173088	Springfield Township	8,965	9,547	8,673	9,229	9,366	9,467	9,626	9,731	9,824	859	9.6%
4209176304	Telford Borough	651	644	604	691	714	729	748	774	785	134	20.6%
4209177152	Towamencin Township	7,673	8,275	7,700	8,983	9,142	9,331	9,503	9,706	9,856	2,183	28.5%
4209177304	Trappe Borough	1,990	2,058	1,933	2,032	2,049	2,065	2,094	2,130	2,181	191	9.6%
4209179008	Upper Dublin Township	20,488	22,949	21,414	22,422	22,712	22,893	23,164	23,444	23,700	3,212	15.7%
4209179040	Upper Frederick Township	871	914	845	963	1,007	1,023	1,027	1,032	1,038	167	19.2%
4209179056	Upper Gwynedd Township	19,506	21,663	20,286	20,489	20,444	20,392	20,395	20,440	20,453	947	4.9%
4209179064	Upper Hanover Township	3,211	3,368	3,064	3,481	3,584	3,625	3,698	3,764	3,823	612	19.1%
4209179136	Upper Merion Township	52,328	57,014	52,379	56,230	57,650	58,146	58,915	59,821	60,724	8,396	16.0%
4209179176	Upper Moreland Township	16,625	17,437	15,930	16,628	16,787	16,893	17,050	17,263	17,449	824	5.0%
4209179240	Upper Pottsgrove Township	1,234	1,226	1,107	1,279	1,336	1,347	1,370	1,389	1,410	176	14.3%
4209179256	Upper Providence Township	22,317	23,774	22,128	24,263	24,773	25,032	25,322	25,733	26,114	3,797	17.0%
4209179280	Upper Salford Township	1,141	1,162	1,052	1,161	1,196	1,222	1,262	1,292	1,318	177	15.5%
4209182736	West Conshohocken Borough	5,857	6,666	6,182	6,628	6,633	6,644	6,678	6,741	6,820	963	16.4%
4209183696	West Norriton Township	9,256	9,931	9,044	9,583	9,743	9,836	9,966	10,104	10,198	942	10.2%
4209183912	West Pottsgrove Township	1,602	1,822	1,622	1,759	1,774	1,784	1,805	1,823	1,834	232	14.5%
4209184624	Whitemarsh Township	19,783	20,372	18,834	19,935	20,245	20,418	20,670	20,945	21,099	1,316	6.7%

(Continued)

											2015-2050	
ID	Municipality or District	2015 Base	2019 Forecast	2020 Forecast	2025 Forecast	2030 Forecast	2035 Forecast	2040 Forecast	2045 Forecast	2050 Forecast	Absolute Change	Percentage Change
4209184888	Whitpain Township	18,560	20,122	18,587	19,739	19,790	19,831	19,935	20,028	20,105	1,545	8.3%
4209186496	Worcester Township	4,326	4,515	4,160	4,612	4,757	4,846	4,974	5,123	5,199	873	20.2%

Source: DVRPC, 2021

Table B-9: Philadelphia County Forecasted Employment by Planning District, 2015–2050

ID	Municipality or District	2015 Base	2019 Forecast	2020 Forecast	2025 Forecast	2030 Forecast	2035 Forecast	2040 Forecast	2045 Forecast	2050 Forecast	2015-2050 Absolute Change	2015-2050 Percentage Change
4210160101	North	38,224	42,804	40,284	40,659	41,146	41,178	41,243	41,276	41,304	3,080	8.1%
4210160102	Lower Southwest	32,834	36,827	34,580	34,930	35,012	35,000	35,069	35,152	35,209	2,375	7.2%
4210160103	Central	262,507	280,742	263,712	274,551	277,818	280,117	281,095	282,048	282,770	20,263	7.7%
4210160104	North Delaware	23,191	27,253	25,781	26,622	26,722	26,784	26,885	26,959	27,010	3,819	16.5%
4210160105	Lower South	19,397	23,703	22,277	27,368	33,940	40,923	44,476	44,945	45,084	25,687	132.4%
4210160106	West Park	16,675	18,159	17,009	17,461	17,557	17,630	17,753	17,844	17,921	1,246	7.5%
4210160107	Lower North	31,758	37,109	34,950	35,492	35,561	35,591	35,648	35,677	35,683	3,925	12.4%
4210160108	Lower Northwest	17,308	18,438	17,143	17,648	17,728	17,807	17,922	17,990	18,023	715	4.1%
4210160109	River Wards	22,627	27,243	25,440	26,675	27,217	27,209	27,244	27,277	27,275	4,648	20.5%
4210160110	University - Southwest	82,039	94,163	91,192	99,118	104,704	108,927	112,425	117,362	129,909	47,870	58.4%
4210160111	West	18,630	20,765	19,586	19,476	19,431	19,413	19,416	19,423	19,437	807	4.3%
4210160112	South	33,564	38,289	35,453	37,265	37,961	38,117	38,298	38,459	38,582	5,018	15.0%
4210160113	Upper Far Northeast	30,496	35,069	33,355	35,042	35,292	35,366	35,503	35,723	35,850	5,354	17.6%
4210160114	Lower Northeast	26,914	28,753	27,376	27,995	28,097	28,303	28,495	28,636	28,721	1,807	6.7%
4210160115	Upper North	30,415	35,415	33,482	34,043	34,175	34,292	34,431	34,536	34,609	4,194	13.8%
4210160116	Lower Far Northeast	29,420	31,444	29,472	30,661	30,949	31,050	31,159	31,291	31,471	2,051	7.0%
4210160117	Upper Northwest	26,952	29,923	28,241	28,894	28,945	29,000	29,082	29,158	29,197	2,245	8.3%
4210160118	Central Northeast	23,212	26,145	25,012	25,580	25,726	25,859	25,991	26,151	26,256	3,044	13.1%

Source: DVRPC, 2021

Appendix C

Additional Information on UrbanSim Development

DELAWARE VALLEY
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Appendix C: Additional Information on UrbanSim Development

Appendix C documents some more detailed information used in UrbanSim development and final model configurations.

Developable Area Calculation

The buildable area of blocks was created in order to calculate block-level capacity constraints for residential units and employment. In order to calculate developable area, the nondevelopable area of each block was subtracted from the overall area. The 2015 DVRPC Land Use Inventory was used to eliminate a number of areas of blocks unlikely to house further growth in employment or residential units. Table C-1 lists by subcategory the land uses excluded from developable area per block.

Table C-1: List of Land Use Subcategories Excluded from Developable Area

Category Code	Category	Subcategory Code	Subcategory
04	Transportation	04000	Transportation: Facility
		04009	Parking - Transportation: Facility
		04010	Transportation: Highway Right-of-Way
		04011	Transportation: Roadway
		04020	Transportation: Rail Right-of-Way
05	Utility	05000	Utility: Right-of-Way
		05010	Utility: Landfill
		05019	Parking - Utility: Landfill
		05020	Utility: Wastewater Treatment
		05029	Parking: Utility: Wastewater Treatment
		05030	Utility: Other Facility
		05039	Parking - Utility: Other Facility
07	Institutional	07050	Institutional: Cemetery
		07059	Parking - Institutional: Cemetery
08	Military	08000	Military
		08009	Parking - Military
09	Recreation	09000	Recreation: General
		09009	Parking - Recreation: General
		09010	Recreation: Golf Course
		09019	Parking - Recreation: Golf Course
13	Water	13000	Water
14	Undeveloped	14020	Drainage Basin

Source: DVRPC, 2019

The other data source used was the DVRPC 2016 Protected Open Space Inventory, with the addition of more recent data received from Chester County for 2017. This included homeowners' association (HOA) land, which was not accounted for in other counties. It made the Chester County parcels more realistically constrained; however, the fact that it doesn't match up with the rest of the region may be reconsidered when the model is updated with new protected open space data and zoning layers.

While capacity is not currently present in locations such as golf courses, a change in capacity to allow redevelopment could be added in a simulation year in order to explore alternative development outcomes.

Explanatory Variables and Uncalibrated Coefficients for Submodels

Table C-2 provides a list of 45 explanatory variables used in the various key submodels of DVRPC's UrbanSim platform. The type of variable is denoted with icons with the following meanings:

- Accessibility
- $ Cost
- Demographics
- Employment
- Residential units
- Environmental

The summary geography used for each submodel and segment is noted, along with the coefficient value (negative coefficients in orange text and positive in green).

Table C-2: Explanatory Variables and Uncalibrated Coefficients in UrbanSim Submodels

Type	Explanatory Variables	Geography Level	REPM		RDPLCM		HLCM								ELCM					
			1	2	1	2	1	2	3	4	5	6	7	8	1	2	3	4	5	6
$	The combined interaction of average rent and households within 30 minutes travel time for an average weekday during the 6:00 to 10:00 am period	block [rent], TAZ [time]*			-0.05															
$	The combined interaction of average rent and employment within 30 minutes travel time for an average weekday during the 6:00 to 10:00 am period	block [rent], TAZ [time]*										0.01	0.16	-0.13						
	Total households within 30 minutes travel time for an average weekday during the 6:00 to 10:00 am period	TAZ*			0.14															
	Total employment within 15 minutes travel time for an average weekday during the 6:00 to 10:00 am period	TAZ*	-1,311.8						0.01											
	Total employment within 15 minutes travel time via transit for an average weekday during the 6:00 to 10:00 am period	TAZ*	11,085.6	18.1																
	Total employment within 30 minutes travel time for an average weekday during the 6:00 to 10:00 am period	TAZ*		15.6		0.19	0.18				0.24	0.14	0.30	0.03	0.58	0.47	0.46	0.36	0.74	0.31

(Continued)

Type	Explanatory Variables	Geography Level	REPM		RDPLCM		HLCM								ELCM					
			1	2	1	2	1	2	3	4	5	6	7	8	1	2	3	4	5	6
	Tier 1 university within 10 minutes travel time for an average weekday during the 6:00 to 10:00 am period	TAZ*		12720.5				0.08		0.12	0.07				0.14			0.06	0.18	0.10
	Tier 2 university within 6 minutes travel time for an average weekday during the 6:00 to 10:00 am period	TAZ*					0.12													
	Travel time to 30th Street Station for an average weekday during the 6:00 to 10:00 am period	block	2,587.6							0.05	0.06		0.08							
	A State route is within 3 to 10 minutes travel time for an average weekday during the 6:00 to 10:00 am period	TAZ*										0.05	0.02							
	A US route freeway interchange is within 3 to 10 minutes travel time for an average weekday during the 6:00 to 10:00 am period	TAZ*				0.02				0.05						0.05			0.05	0.04
	An Interstate interchange is within 5 to 15 minutes travel time for an average weekday during the 6:00 to 10:00 am period	TAZ*						0.08							0.13					
$	Average residential unit value	block*					-0.20	-0.11												
$	Average rent	block*			0.06	0.15					-0.06	-0.13	-0.08	0.00						
$	Standard deviation of residential unit values	MCD-CPA*^										-0.07								

(Continued)

Type	Explanatory Variables	Geography Level	REPM		RDPLCM		HLCM								ELCM					
			1	2	1	2	1	2	3	4	5	6	7	8	1	2	3	4	5	6
	Ratio of employment to households	block group*^			-0.43										0.20	0.36	0.42	0.35	0.48	0.34
	High poverty (average income is less than $40,000 [2015$]), high renter (55% of households rent), high zero car households (average cars per household is less than one), with older residents (average age of household head is 55 years or greater), and older residential units (average year built is earlier than 1950).	block*	-1,152.3	-13.8										0.04						
	High wealth (average household income is at least $100,000 [2015$] a year), high owner occupancy (80% of units or more) in older construction (average year built is before 1955)	block*				-0.09		0.41			-0.19	-0.21	-0.31	-0.19						
	Ratio of households to residential units	block group*								0.08										
		MCD-CPA*	-7,012																	
	Average age of household head	block group*			0.13	0.06	-0.39	0.40	-0.17	0.43		0.31								
	Average household income	MCD-CPA*^				0.08														
		tract*	133,892.2	189.5																
	Average number of children per household	block group*					-0.50	-0.39	0.07				0.10							

(Continued)

Type	Explanatory Variables	Geography Level	REPM		RDPLCM		HLCM								ELCM					
			1	2	1	2	1	2	3	4	5	6	7	8	1	2	3	4	5	6
	Household density (households per square meter) within land area of geography	block*^													-0.60	-0.76	-0.64	-0.17	-0.26	-0.58
		tract*	3,860.7																	
	Proportion of two-car households	block*								0.27										
	Proportion of three-car households	block*							0.17											
	Proportion of households below poverty level	MCD-CPA*^														-0.25	-0.15	-0.15	-0.52	-0.12
	Proportion of households owning their home	block group*													-0.15	-0.14		-0.13	-0.04	-0.23
	Proportion of households renting their home	block*			0.20	0.91	-0.52													
	Proportion of households with 3 workers	MCD-CPA*^						-0.11			-0.26									
	Proportion of households with 5 children	MCD-CPA*^													-0.09					
	Proportion of households with income within the 10th percentile (lowest 10 percent of records)	TAZ*					-0.21		-0.47											
	Sum of population aged 15 to 18	MCD-CPA*^					0.07													
	Employment density (employment per square meter) within land area of geography	block*^				0.18														
		block group*^	3,703.3	39.3																
	Proportion of employment in the Basic industries (agriculture, forestry/fishing, mining, construction, manufacturing) sectors	block*														0.83				

(Continued)

Type	Explanatory Variables	Geography Level	REPM		RDPLCM		HLCM								ELCM					
			1	2	1	2	1	2	3	4	5	6	7	8	1	2	3	4	5	6
	Proportion of employment in the Finance, Insurance, and Real Estate sectors	block*																	0.62	
	Proportion of employment in the Management and Public Administration sectors	block group*													0.57					
		MCD-CPA*^				-0.10	0.13		-0.14					0.10						
	Proportion of employment in the Retail Trade sectors	block*																0.86		
		MCD-CPA*^								-0.09										
	Proportion of employment in the Services sectors	block*																		0.97
	Proportion of employment in the Transportation, Communications & Public Utilities, Warehousing sectors	block*															0.61			
	Sum of employment from federal government or military	MCD-CPA*^					-0.10	-0.08												
	Percent of developable land in 100-year floodplains	block*		-8.8											-0.61	-0.69	-0.75	-0.61	-0.69	-0.72
	Average year built	block group*						0.42		0.44					0.09	0.34	0.38	0.30	0.47	0.23
		tract*		75.8																
	Number of owned single-family homes with a year built of 2010 or later.	block*^			0.22															
	Residential units constructed in the past 5 years	TAZ*					0.03	0.03												

(Continued)

Type	Explanatory Variables	Geography Level	REPM		RDPLCM		HLCM								ELCM					
			1	2	1	2	1	2	3	4	5	6	7	8	1	2	3	4	5	6
	The most frequent residential unit type is rental multifamily units	block*	6,618																	
	Total residential units	block*^					1.89	1.72	1.47	1.57	2.43	2.74	2.13	2.35						

Source: DVRPC, 2020

** The standardized form of variable was used (the mean was subtracted from the variable and then the result was divided by the standard deviation).*

^ The natural log of the variable is used.

Control Totals

Control totals used for the final 2019–2050 simulations are found in tables C-3 and C4.

Table C-3: Subregion Household Control Totals

Year	Four New Jersey Counties	Four Suburban Pennsylvania Counties	Philadelphia
2019	591,568	959,179	625,068
2020	593,377	962,364	627,977
2021	596,434	966,940	632,303
2022	599,034	972,526	636,354
2023	601,334	977,526	638,303
2024	603,434	982,181	640,253
2025	606,187	986,491	642,640
2026	608,542	990,545	645,592
2027	610,574	994,391	648,011
2028	612,357	998,077	650,261
2029	613,966	1,001,651	651,339
2030	615,476	1,005,161	652,223
2031	616,871	1,008,524	652,976
2032	618,172	1,011,767	653,679
2033	619,401	1,014,918	654,343
2034	620,580	1,018,005	654,980
2035	621,730	1,021,055	655,601
2036	622,800	1,023,996	656,179
2037	623,805	1,026,849	656,722
2038	624,760	1,029,634	657,238
2039	625,680	1,032,371	657,735
2040	626,580	1,035,081	658,221
2041	627,416	1,037,636	658,672
2042	628,200	1,040,065	659,095
2043	628,944	1,042,397	659,497
2044	629,660	1,044,661	659,884
2045	630,360	1,046,886	660,262
2046	630,996	1,049,007	660,862
2047	631,580	1,051,043	661,884
2048	632,124	1,053,014	662,906
2049	632,640	1,054,940	663,682
2050	633,140	1,056,840	664,458

Source: DVRPC, 2021

Table C-4: Regional Employment Sectoral Control Totals, 2019–2050

	11	21	22	23	31	32	33	42
Year	Agriculture, Forestry, Fishing & Hunting	Mining, Quarrying, & Oil & Gas Extraction	Utilities	Construction	Manufacturing (Non-Durable Goods)	Manufacturing (Mostly Non-Durable Goods)	Manufacturing (Durable Goods)	Wholesale Trade
2019	10,067	859	10,949	154,867	36,957	83,267	131,798	122,077
2020	10,067	750	10,253	137,582	35,116	80,907	127,189	115,505
2021	9,952	780	10,066	149,151	36,672	85,296	127,949	116,027
2022	9,831	816	10,781	153,988	36,227	85,639	128,577	116,709
2023	9,778	813	10,744	156,082	36,047	86,804	126,958	117,544
2024	9,714	810	10,704	157,409	35,856	88,381	125,307	116,406
2025	9,663	808	10,672	159,207	35,690	89,392	123,751	115,354
2026	9,622	806	10,649	159,469	35,558	91,127	122,317	114,413
2027	9,584	804	10,625	159,711	35,423	92,398	120,875	113,464
2028	9,560	804	10,623	160,272	35,358	93,434	119,678	112,742
2029	9,546	805	10,635	161,055	35,342	93,907	118,645	112,177
2030	9,534	805	10,642	161,754	35,308	94,343	117,548	111,551
2031	9,525	806	10,646	162,309	35,265	94,788	116,424	110,900
2032	9,509	806	10,651	162,864	35,223	95,372	115,299	110,249
2033	9,494	806	10,654	163,402	35,177	95,953	114,161	109,585
2034	9,480	806	10,655	163,908	35,124	96,592	113,000	108,900
2035	9,457	806	10,655	164,393	35,067	97,319	111,824	108,200
2036	9,443	806	10,656	164,797	35,013	98,102	110,660	107,512
2037	9,429	806	10,655	165,180	34,954	98,901	109,481	106,810
2038	9,417	806	10,655	165,568	34,897	99,723	108,306	106,111
2039	9,406	806	10,655	165,969	34,842	100,607	107,140	105,420
2040	9,395	807	10,656	166,374	34,789	101,506	105,976	104,732
2041	9,389	807	10,658	166,743	34,738	102,410	104,820	104,052
2042	9,384	807	10,660	167,110	34,686	103,352	103,662	103,370
2043	9,378	807	10,661	167,467	34,632	104,294	102,497	102,682
2044	9,373	807	10,661	167,813	34,576	104,370	101,326	101,987
2045	9,370	807	10,663	168,186	34,526	104,443	100,171	101,308
2046	9,369	807	10,666	168,535	34,480	104,543	99,029	100,644
2047	9,368	808	10,670	168,891	34,437	104,647	97,891	99,983
2048	9,370	808	10,675	169,267	34,396	104,787	96,763	99,333
2049	9,371	808	10,681	169,644	34,356	104,931	95,635	98,683
2050	9,371	809	10,686	169,977	34,317	105,078	94,508	98,035

(Continued)

Year	44–45 Retail Trade	48–49 Transportation & Warehousing	51 Information	52 Finance & Insurance	53 Real Estate & Rental & Leasing	54 Professional, Scientific, & Technical Services	55 Management of Companies & Enterprises	56 Administrative & Support & Waste Management & Remediation Services
2019	294,324	123,145	79,759	182,443	96,206	319,602	6,231	271,506
2020	279,763	117,227	76,951	179,668	92,847	308,020	5,764	262,792
2021	275,462	134,080	78,029	181,460	93,267	318,603	5,791	269,207
2022	268,742	142,238	78,927	180,345	90,991	322,901	6,033	267,739
2023	264,615	149,665	78,775	180,078	89,593	330,410	6,142	270,089
2024	259,164	156,742	78,596	179,751	87,748	336,419	6,144	271,073
2025	253,303	163,105	78,472	179,547	86,191	340,264	6,149	271,534
2026	249,528	169,467	78,420	179,510	85,328	343,529	6,161	272,809
2027	246,868	175,168	78,360	179,451	84,419	348,322	6,172	273,929
2028	245,965	180,604	78,456	179,751	84,110	352,227	6,194	275,643
2029	244,770	185,114	78,660	180,299	84,116	355,762	6,226	277,037
2030	243,688	187,815	78,824	180,754	84,089	359,185	6,254	278,325
2031	243,268	188,997	78,971	181,170	84,068	362,664	6,281	279,637
2032	242,839	190,179	79,117	181,587	84,167	364,900	6,308	281,360
2033	242,913	191,342	79,255	181,983	84,261	367,121	6,335	283,074
2034	242,805	192,469	79,378	182,345	84,402	369,566	6,360	284,676
2035	242,990	193,569	79,491	182,682	84,617	371,243	6,384	286,537
2036	243,270	194,690	79,612	183,040	84,536	373,116	6,409	288,553
2037	243,609	195,786	79,722	183,372	84,467	375,041	6,433	290,618
2038	243,641	196,888	79,835	183,711	84,408	377,031	6,457	292,742
2039	243,817	198,005	79,954	184,064	84,399	378,493	6,482	294,753
2040	243,953	199,128	80,075	184,422	84,394	379,985	6,507	296,798
2041	244,184	200,267	80,203	184,795	84,387	381,469	6,533	298,846
2042	244,033	201,402	80,329	185,164	84,405	383,075	6,558	301,002
2043	243,947	202,525	80,450	185,522	84,415	384,653	6,583	303,143
2044	244,103	203,637	80,567	185,869	84,476	386,471	6,608	305,485
2045	244,252	204,780	80,696	186,246	84,534	388,284	6,633	307,223
2046	244,464	205,954	80,837	186,649	84,615	390,210	6,660	309,055
2047	244,685	207,138	80,981	187,061	84,700	392,160	6,687	310,908
2048	244,992	208,346	81,135	187,495	84,814	394,254	6,715	312,256
2049	245,305	209,556	81,289	187,929	84,930	396,371	6,743	313,621
2050	245,627	210,774	81,446	188,370	85,049	398,512	6,771	315,002

(Continued)

Year	61 Educational Services	62 Health Care & Social Assistance	71 Arts, Entertainment, & Recreation	72 Accommodation & Food Services	81 Other Services (except Public Administration)	92 Public Administration (State & Local)	92 Public Administration (Federal)	n/a Armed Forces
2019	273,092	453,837	62,122	229,671	168,696	119,802	27,827	18,925
2020	256,170	440,525	43,207	163,118	146,064	123,186	28,103	18,925
2021	261,149	457,850	45,121	175,212	149,629	122,518	27,950	18,779
2022	267,047	462,726	55,560	195,830	150,940	121,225	27,655	18,532
2023	266,487	466,480	59,963	211,727	154,450	120,815	27,561	18,378
2024	265,838	469,947	63,379	223,790	155,761	120,364	27,459	18,239
2025	265,372	473,610	64,103	230,701	157,541	119,999	27,375	18,195
2026	265,153	477,591	64,090	235,176	159,053	119,745	27,317	18,162
2027	264,904	481,402	64,353	236,142	159,706	119,478	27,257	18,148
2028	264,989	482,849	64,437	236,448	159,913	119,450	27,250	18,172
2029	265,440	484,967	64,763	236,939	159,609	119,588	27,282	18,212
2030	265,753	486,834	65,019	237,333	159,239	119,663	27,299	18,262
2031	265,960	488,596	65,319	237,744	158,880	119,712	27,310	18,281
2032	266,167	490,360	65,644	238,499	158,752	119,761	27,321	18,285
2033	266,345	492,071	65,870	239,237	158,454	119,797	27,329	18,298
2034	266,472	493,689	66,143	240,115	158,245	119,811	27,332	18,346
2035	266,562	495,239	66,396	241,206	158,175	119,807	27,332	18,369
2036	266,682	496,844	66,766	242,422	158,183	119,817	27,334	18,400
2037	266,766	498,383	67,148	243,673	158,209	119,811	27,332	18,431
2038	266,859	499,937	67,543	244,966	158,261	119,809	27,332	18,463
2039	266,972	501,532	67,950	246,405	158,398	119,816	27,334	18,495
2040	267,093	502,894	68,461	247,868	158,548	119,826	27,336	18,543
2041	267,235	504,297	68,799	249,331	158,692	119,846	27,340	18,585
2042	267,371	505,690	69,112	250,880	158,884	119,863	27,344	18,640
2043	267,502	507,055	69,533	252,414	159,064	119,874	27,347	18,691
2044	267,616	508,388	69,941	254,112	159,339	119,877	27,348	18,744
2045	267,773	509,606	70,871	255,813	159,607	119,899	27,353	18,806
2046	267,910	510,898	71,569	257,593	159,921	119,938	27,361	18,877
2047	268,058	512,214	72,120	259,395	160,240	119,983	27,372	18,923
2048	268,188	513,589	72,564	261,299	160,614	120,041	27,385	18,965
2049	268,319	514,966	72,907	263,225	160,994	120,099	27,398	19,021
2050	268,459	516,362	73,162	265,174	161,381	120,162	27,413	19,071

Source: DVRPC, 2021

Appendix D

Base Employment Data Preparation

Appendix D: Base Employment Data Preparation

NETS Procurement Background

Base employment data for forecasting primarily comes from the National Establishments Time-Series (NETS), a proprietary product of Walls & Associates. NETS data provides the point location of establishments or firms as well as their six-digit North American Industrial Classification System (NAICS) code and employment count by year, similar to other proprietary employment data products (Data Axel, Dun & Bradstreet). Since 2012, DVRPC has purchased it for base data needs of the employment forecast, as well as other agency analysis needs.

Forecasts prior to DVRPC's purchases of NETS data relied on the Census Transportation Planning Products (CTPP) Part 2 Workplace geography. While the CTPP supplied all the 14 sectors of employment needed to run the travel model, it aggregated individual employers' employment to totals by common geography, in this case, travel analysis zones (TAZ) for travel model use and municipal or Philadelphia Planning District levels for the employment forecast. When last used as the sole forecast input, the CTPP was based on the Decennial "long form" Census of 2000, where a nearly complete count of the population and its workers were collected. With the discontinuation of the long form decennial count, and the transition to more detailed demographic data collection from the American Community Survey (ACS), the CTPP transitioned to creating a special tabulation of ACS data to collect information on workers and commuting based on survey questions on where household workers are employed, their means of transportation, and other inquiries. The smaller sample size of the ACS created larger margins of error (MOE) and a less reliable picture of workers surveyed by household. The 2013 release of the first ACS-based CTPP dataset (the 2006–2010 period estimates) falling after the 2010–2040 forecast work was being conducted in 2012, made continued use of the CTPP for agency needs untenable.

With CTPP employment no longer an option, DVRPC staff researched and compared several sources of employment data, including government sources (such as ES-202 data, the Bureau of Labor Statistics' Quarterly Census of Employment and Wages, and the Current Employment Statistics survey) and private proprietary sources. NETS was determined to be superior to other sources in terms of coverage, accuracy, and the provision of locational data. DVRPC staff continue to monitor employment data products but so far have not found a more compelling product, particularly after creating some reliance on prior forecasts efforts to clean up new NETS releases.

The NETS database is essentially a "cleaned-up" version of the Dun and Bradstreet database.

> *Founded in 1841, Dun & Bradstreet, Inc. (D&B) is a business services company that provides commercial data and analysis services to businesses on credit history, business-to-business sales and marketing, risk exposure, and supply chain management. In 1963, D&B introduced the DUNS, which is a unique nine-digit numeric identifier assigned to each business location in the D&B master business database. Although not mandatory, DUNS has become the de facto worldwide standard for establishing a business credit file, which is used by lenders and potential business partners to help predict the financial stability of a company. The United States Government, the European Commission, and the United Nations require all grant applicants and contractors to have a DUNS number; and more than 50 global industry and trade associations recognize, recommend, or require that their members obtain a DUNS number.*[2]

Using each company's unique DUNS number (or numbers, in cases where separate divisions within a company have unique DUNS numbers), Walls & Associates creates a time series for each business and then screens the data to eliminate duplicates and identify anomalies. If a file contains suspicious information, the data is cross-checked with previous annual records and adjusted or eliminated as appropriate, based on information collected

[2] NCHRP 08-36, Task 127 Employment Data for Planning A Resource Guide (apps.trb.org/cmsfeed/TRBNetProjectDisplay.asp?ProjectID=3686)

from other sources (including government and nonprofits). One advantage of the establishment-based NETS Database is that all employment, sales, and other activity is reported at the actual facility—not the headquarters.

Unlike government sources of employment data, the NETS database includes sole proprietors, part-time employment, and farm operations, and has been found to be more accurate in reporting data for small privately-owned firms and public sector employers such as post offices and public schools. Employment from the NETS database is therefore generally higher than many of these other sources. DVRPC adds CTPP Armed Forces estimates at the TAZ level to overall employment, as that employment type is unaccounted for in NETS data.

The 2015 NETS database was purchased for the 2015–2050 forecast (2050 v1.0). The 2015–2045 forecast was created prior to the 2015 NETS release. That forecast relied on 2010 and 2013 NETS data extrapolated to 2015. The 2010–2040 forecast relied on the 2010 NETS release.

NETS Processing and Cleaning

Despite the advantages of NETS data, its half a million establishments in the region require further review and cleanup after purchase. DVRPC has established and refined internal cleanup procedures to correct NETS records prior to then sharing the data for a limited time with county partners, via the Socioeconomic and Land Use Analytics Committee (SLUAC), for their own review and recommended changes. The 2015 NETS product came with employment counts at firm locations for 1990 through 2015. The attributes of each year are intended to be a snapshot of conditions on January 1. Recent prior years of NETS data were used to create relocation rates of businesses by sector to inform the relocation submodels in the UrbanSim model. However, since 2015 aligned with the forecast base year it underwent all DVRPC staff and county scrutiny.

Processing and cleaning the 2015 NETS employment data was accomplished in seven general steps. These are further detailed in the following sections.

1. Database setup;
2. Geocoding firm locations;
3. Rescaling: Applying adjustments from prior datasets;
4. Flagging records to prioritize manual review;
5. Manual review;
6. Final steps before county review; and
7. County review and reconciling changes.

1. Database setup

The newly purchased 2015 NETS release was moved into a database containing DVRPC's previously cleaned 2013 NETS database with the adjustments made in the last forecast round in order to carry forward the benefit of prior cleaning efforts.

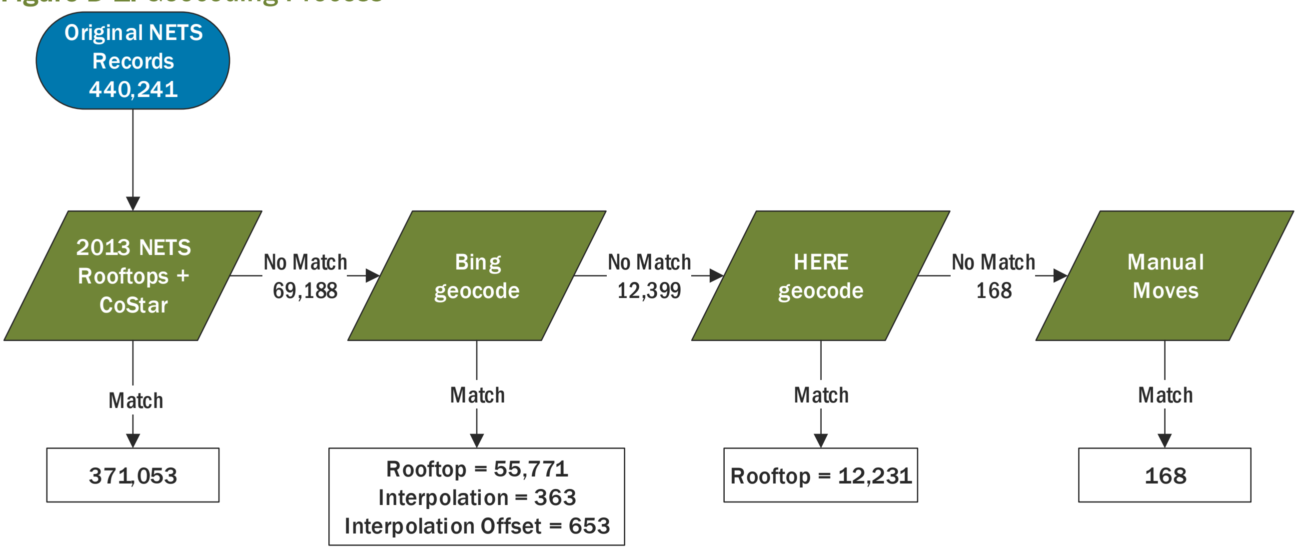
2. Geocoding firm locations

NETS data comes with latitude and longitude coordinates for each record in each year. DVRPC has improved the locational accuracy of firms over the years by geocoding locations based on address information that is native to the dataset.

For the 2015 NETS, a table of coordinates was developed combining the rooftop matched addresses from prior NETS purchases with coordinates from property records from DVRPC's CoStar commercial real estate data—a proprietary dataset purchased as an ongoing subscription. CoStar coordinates have proved highly accurate in most cases. Address data in CoStar is largely consistent and standardized in form, but NETS address data can be very irregular due to data entry from multiple sources. A street with the prefix or suffix "North" could be entered as "North" or "N". "Lane" could be "Lane," "Ln," or "La." Street names and cities can be abbreviated or simply misspelled. Opensource tools Libpostal[3] and Pypostal[4] were employed to get NETS and CoStar addresses into a consistent pattern and nomenclature. Once standardized, the list of coordinates for each unique address from the best prior NETS records and CoStar records were then joined to the standardized 2015 NETS records by address string. This process was effective for more than 84 percent of the 440,241 2015 NETS records.

The remaining 69,158 records were geocoded using Bing Maps or HERE geocoding. Figure D-1 is a flow chart displaying the processing of these records.

Figure D-1: Geocoding Process



Source: DVRPC, 2019

Nonrooftop results for any record with five or more employees then underwent individual review. Locations that could be improved were manually moved to more accurate locations.

NETS points were assigned to respective higher geographies of county, municipality or Philadelphia Planning District, tract, block group, and block that they intersected with. This aided later aggregations, including oversight of the manual review process.

3. Rescaling: Applying adjustments from prior datasets

With each NETS purchase, DVRPC staff have carried forward adjustments made to prior datasets into the most recent. For the 2015–2045 forecast a 2015 release was not available. 2013 was the closest year to the base year, and the 2010 and 2013 years were improved through staff and county review before applying interpolation methods to estimate a base year by TAZ. Sometimes these adjustments zeroed out records previously deemed duplicative, and others rescaled the employment value to a higher or lower level than initially reported due to better information or blanket assumptions about groups of records.

Nine percent of records were rescaled—a net reduction of 6 percent of the original employment total geocoded to the region. Fifteen percent of records were zeroed out, reducing the original 2015 NETS employment by 14 percent.

[3] github.com/openvenues/libpostal
[4] github.com/openvenues/pypostal

There were a number of records from the prior 2013 NETS purchase that did not show up in either the 2013 or 2015 records from the 2015 NETS purchase. These records were appended into the database with 2013 employment values as 2015 values to be evaluated among the rest of the records. This seemed important as staff didn't want to lose businesses that may not have closed.

4. Flagging records to prioritize manual review

Due to the magnitude of NETS records in our region and limited resources to comb through each one, records were flagged in order to identify which would have the highest priority to examine internally before passing on to county staff for their review. Table D-1 explains the various "flags" present in the NETS delivery or created by DVRPC staff in order to identify records falling into particular categories that helped staff rationalize the priority of which records would receive a manual review.

Table D-1: Flagged Record Categories

Flag	Explanation
Zeroed	Records zeroed out due to zeroing out employment for them in prior NETS purchases. These were excluded from review.
'Status' = Closed	NETS 'Status' field contains "Closed", representing that the business had closed by 2015. These were excluded from review.
'Status' = New	NETS 'Status' field contains "New", indicating the firm was added since 2013.
'Status' = Moved	Businesses with a new location than in 2013.
'Status' = [blank]	NETS Status field was blank and therefore status was unknown.
Rescaled, high gains	The two-year change from rescaled 2013 and 2015 employment was greater than 100.
Delivery, high gains	The two-year change from 2013 and 2015 employment as delivered was greater than 100.
Suspected duplicate	Record shares the same headquarters ID (HQDUNS), NAICS code, address, and employment count as another record.
Large employer	Employment count is greater than 100.
Large public/edu branch	Record is a public sector or educational location with 100 or more employees and shares a HQDUNS with other records in the region. This was to address the known issue of potential duplication of employment at headquarters and branches observed from municipal agencies or departments of education in the past.

Source: DVRPC, 2019

5. Manual review

Flagged priorities

The manual review process was performed by a single staff person under the oversight of two others. Main groupings of records were bundled to focus attention on one record type at a time, increasing efficiencies by reducing the orientation time to each record and what might be going on with it. The following major groupings were used for manual review (see also Table D-1):

1. Rescaled, high gains (that stayed at 2013 location);
2. New;
3. Moved;
4. Status = [blank]; and

5. Other.

Among the major groups, records were further partitioned into those records:

1. not flagged as large public sector branch; and
2. large public sector branch.

The potential magnitude of impact review could have in changing overall employment totals drove the prioritization within each of these subgroups. In each of these, priority was given to any:

1. Large employer;
2. Suspected duplicate; and
3. Large gains before rescaling

Combinations of the above were treated first, then single priority records. Often, the completion of any of these three categories within a main group meant moving on to the next group, as time spent on smaller, nonsignificant growth, nonduplicate suspects would be less effective.

The actual review of records often involved comparisons of employee counts of companies at particular locations reported by NETS with other sources of information. Publicly available sources included:

- Googling company info;
- company/agency websites;
- Wikipedia;
- Manta;
- LinkedIn;
- Buzzfile;
- Hoovers;
- Bloomberg; and
- Publications: articles and reports

A key proprietary source for checking NETS records was DVRPC's subscription to the CoStar commercial real estate database. CoStar tracks information like building tenants and total building and tenant-leased square footage. Less reliably, employment counts are available for building tenants. With information on square footage, even without employment counts, the ratio of a company's employment (sum of NETS employment of firm at address) to space for that tenant from CoStar. Alternatively, the aggregation of all NETS records at the building address and the full building square footage from CoStar can be compared. Depending on the building type, the ratio of employment to square feet can really vary and there can be particular considerations about tenants that could change what ratio may be reasonable, for instance a facility with workers around the clock or multiple shifts may have higher employment counts than those with smaller windows of operation where all employees tend to occupy the space at once.

One company can exist with multiple industry codes at the same address. As a result, care was taken when reducing potential duplicates or high values so as to not wipe out entire sectors that exist within a company.

While work was performed, summaries of records changed were logged by flag type combinations, by county, and by municipality so that oversight staff could monitor the status of the effort and ensure that counts were in a reasonable range by geography relative to the 2013 NETS and public sources of employment counts by county.

Additional Checks

From experience gained while processing other NETS purchases, DVRPC staff took additional steps to ensure 2015 records were scrutinized from particular angles. Table D-2 explains these additional checks.

Table D-2: Additional Review Types

Flag	Explanation
Ports and freight facilities employment	Staff from DVRPC's Office of Freight and Aviation reviewed 2015 employment at freight and port facilities to ensure the numbers were in line with other sources.
PHL Airport	DVRPC staff ensured coordinates were placed at the terminal, not the location of the employee parking lot that is often listed for airport employees. Presence of each major airline and appropriate relative magnitude of employment was checked. Philadelphia Planning Commission staff felt the prior forecast was short a couple thousand employees based on a later review of NETS data. DVRPC improved airport employment with this in mind, but Philadelphia's staff made significant changes in their later review (this is further discussed in the county review section).
Companies with past importance from counties	County partners in the past had pointed out a handful of companies at locations whose total employment should be in the ballpark of a particular target. DVRPC staff reviewed the proximity to those targets.
Temp, janitorial, and security service companies	These types of businesses can locate contracted employees that serve throughout the region (or outside of it) at the single location of the firm that hires them. The following NAICS codes were checked for the 60 records that had 100+ employees: • 561310: Employment placement agencies and executive search services; • 561320: Temporary help services; • 561612: Security guard and patrol services; and • 561720: Janitorial Services. Employment was adjusted downward to suit the square footage capacity for the building or leased space where the firm was located.

Source: DVRPC, 2019

6. Final steps before county review

Adding CTPP Records

As mentioned, the NETS database does not include Armed Forces employment. This unique form of employment, where enlisted soldiers are often stationed at bases and the workplace is also a residence, can fluctuate greatly due to deployments in domestic or international locations. Federal Base Realignment and Closure Commission (BRAC) changes have impacted bases in the region, such as the merger of McGuire Air Force Base, Fort Dix, and Naval Air Engineering Station Lakehurst into Joint Base McGuire–Dix–Lakehurst in 2009 or the closure of Naval Air Station Joint Reserve Base Willow Grove (NASJRB Willow Grove) in 2011. The latter initiated a master plan to replace the base employment with civilian housing and employment impacting the later years of the population and employment forecast.

The reliability of the CTPP at small geographies can be fairly poor, especially highly stratified variables like workers by 14 different industry groupings at workplace geography. The odds of the ACS sampling a household with a worker in the relatively obscure Armed Forces industry are low, and MOE for locating those surveyed at their place of work geography further increases the MOEs. Of the 59 workplace TAZs in the region containing Armed Forces estimates in the 2012–2016 ACS, the MOEs averaged 145 percent of the estimate; only 13 had MOEs lower than the estimate itself. The data quality is poor, but it serves as a baseline for distribution of Armed Forces employment for the region.

To add further presence of Armed Forces employment that may have been unsampled in the 2012–2016 ACS, the TAZ results of the 2006–2010 ACS was also reviewed. If the employment value at the location was just as plausible as being not present in the 2012–2016 ACS, the earlier dataset's value was used.

The coordinate location of the TAZ's geographic center point (centroid) was used as the location of the employment. The data was entered into table conforming to the NETS 2015 table schema and appended into the NETS GIS file. For 'DUNSNUMBER' each record had the prefix "AF_" followed by the TAZ ID number for the estimate.

Institutions review

An 'Institutions' column was added to the NETS dataset to flag records belonging to the same university, hospitals, or military base. Universities and campuses included:

- Drexel University's University City campus
- Jefferson University's Center City campus
- Princeton University
- Rutgers University's Biomedical and Health Sciences Stratford campus
- Rutgers University's Camden campus
- Temple University's Ambler campus
- Temple University's Fort Washington campus
- Temple University's North Philadelphia campus
- University of Pennsylvania's University City campus
- Villanova University

Hospital institutions included:

- Children's Hospital of Philadelphia
- Jefferson Hospital for Neuroscience/Wills Eye Hospital
- Temple University Hospital
- University of Pennsylvania Hospital

Military institutions included:

- Horsham Air Guard Station (a remnant of the former NASJRB Willow Grove)
- Joint Base McGuire–Dix–Lakehurst
    - Fort Dix
    - McGuire Airforce Base
- Naval Support Activity facility in North Philadelphia
- Naval Surface Warfare Center at the Navy Yard

Institutions review consisted of researching best estimates of total employment at various campuses and facilities and using them as control totals to which NETS records of that institution would sum. Review of the Joint Base McGuire–Dix–Lakehurst not only partitioned the employment by two of the three bases needed within the Joint

Base (the Lakehurst portion is outside the Greater Philadelphia region in Ocean County, NJ), but additionally partitioned into Armed Forces and civilian employment based on a report on all New Jersey military facilities.[5]

Missing NAICS assignment

More than 18,000 NETS records had no NAICS code to indicate its industrial sector. At least the first two digits of the six-digit codes are necessary to assign for the purpose of travel modeling, and the freight model requires at least the first three digits of manufacturing employment (NAICS 31-33) to be assigned to each of those records. Consequently, staff devised ways of assigning likely codes to records. This was done in a number of ways. Grouping missing NAICS records with other records sharing the same 'HQDUNS', allowed the most frequently entered six-digit NAICS code or the one with the largest share of employment to populate any that were missing. For those with all records sharing an HQDUNS having no NAICS code and those with no fellow HQDUNS in the region, a geographic grouping by block or TAZ allowed population of each record-by-record frequency or employment share in the general vicinity. Those records that underwent institution review were populated first, in the context of the institution review and the likelihood of particular NAICS codes flagged for the same institution.

Pre-County Review Results

Table D-3 shows the number of records reviewed by priority level and main grouping of the post-rescaling manual review process. It also shows the net impact those edits made to the NETS employment count. Clearly, the high-to-medium priority records received the highest percentage of completed reviews. 'Status' = [blank] and Other were the main groupings that had the least percentage of higher priority record review. This was largely because they were left to the later stages of the manual review process (least prioritized) and staff time and effort was finite.

The count of low priority records is higher than those with a higher priority. This may seem counter intuitive, or inefficient, but most of that review came from investigating a record with a high priority and having to reconcile it among many lower priority records in the process. This was particularly true of larger companies or institutions where multiple records at the same location had to be reviewed at once. Reviewed simply means it was changed or verified as a good count. The magnitude of change gleaned from the higher priority records versus lower and overall is apparent in the net impact columns.

[5] recon.rutgers.edu/wp-content/uploads/2014/03/NJ_Military_Missions_Economic_Impact2013.06.271.pdf

Table D-3: Results of Post-Rescaling/Zeroing Staff Review

Priority Level	Main Grouping	Records Reviewed		Net Impact of Edits to Total Employment after Rescaling/Zeroing	
		Count	Percentage of Group	Absolute Change	Percentage Change
High-to-medium	Rescaled, high gains	186	100%	-101,221	-3.1%
	‘Status’ = New	304	100%	-136,539	-4.2%
	‘Status’ = Moved	58	100%	-9,227	-0.3%
	‘Status’ = [blank]	137	62%	23,551	0.7%
	Other	228	32%	-42,655	-1.3%
	Armed Forces[6]	*115*	*100%*	*13,463*	*n/a*
	Total	**1,028**	**62%**	**-266,091**	**-8.1%**
Low	Rescaled, high gains	3	6%	1,284	0.0%
	‘Status’ = New	586	1%	671	0.0%
	’Status’ = Moved	25	1%	-133	-0.0%
	’Status’ = [blank]	63	2%	22,704	0.7%
	Other	2,469	1%	-82,411	-2.5%
	Total	**3,146**	**1%**	**-57,885**	**-1.8%**
Total Records		**4,174**	**1%**	**-306,053**	**-9.3%**

Source: DVRPC, 2019; NETS 2015

7. County review and reconciling changes

When DVRPC was ready to share revised records for county review, the first SLUAC meeting was convened. At the meeting, Montgomery County planning staff who were well-versed in NETS reviews from prior purchases, shared the steps taken and tips learned from their last review experience with the other counties.

Counties were given the opportunity to add records for companies that may have been missing in the NETS dataset, as well as revise employee counts. Many counties did a mixture of the two. The Philadelphia City Planning Commission (PCPC) staff ensured that particular areas, such as the Navy Yard and the airport, matched up with external sources. Philadelphia International Airport records of badged employees were used to fill in gaps for airlines and vendors that were not found in the NETS dataset. Also, PCPC questioned reductions to small business records made by DVRPC in prior NETS purchases. DVRPC staff agreed to restore smaller employers as originally reported in the NETS release, unless changed for some other reason. This increased all county employment counts, but Philadelphia in particular.

After counties performed their reviews, DVRPC staff reconciled requested changes and finalized the NETS dataset for base employment in the UrbanSim model.

[6] Armed Forces employment was not part of the original NETS delivery or rescaled values. As described, it was added in using CTPP data by TAZ centroid location, then underwent review to fit to outside sources for enlisted military personnel at base facilities.

Appendix E

Factors Influencing Development in Our Region: Summary of Survey Results

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Appendix E: Factors Influencing Development in Our Region: Summary of Survey Results

In late June and early July 2019, DVRPC conducted a survey directed at contacts in the development review and real estate development communities to obtain feedback on what factors influence real estate development in the region. The primary goal was to prioritize potential regression analysis into "explanatory variables" for the UrbanSim land use model for Greater Philadelphia currently under development. The consultants building the model will use the survey results to determine if there is a strong negative or positive relationship between (1) certain factors respondents found important and (2) existing development patterns. Where stated development factors and existing development patterns agree, the consultants will create a negative or positive coefficient related to that factor at census block level (the smallest unit of geography in the land use model).

The first questions asked background information on development experience. The survey was then structured into three areas associated with development sites, exploring the importance of various:

1. Policies, Incentives, Other Costs
2. Physical Characteristics of a Site
3. Proximity & Access to the Site

There were 53 respondents, primarily from the public sector or consultants that support public sector plan review, but some from the public sector who are involved with the development process, along with nonprofits involved with land use (see Table E-1).

Table E-1: Participants by Category

Category	Response	Count
Public sector planner	n/a	30
Private sector developer	n/a	4
Nonprofit developer	n/a	0
Other (Please specify)	Consultant	5
	Architect	3
	Attorney practicing in real estate and land use	1
	Builder/Construction	1
	MEP/Structural Engineering Firm	1
	Public Sector Engineer	1
	Public sector preservationist	1
	Retired; former public sector planner	1
	Nonprofit land use planning and policy	2
	Nonprofit transportation planner	1
	Nonprofit Conservation organization	1
	Urban Designer for business improvement district	1
	Total	**53**

Source: DVRPC, 2019

The second question asked "In which of the nine counties in the DVRPC Region have you've worked? (Check all that apply)." The respondents had good coverage of all nine DVRPC counties (see Table E-2).

Table E-2: Counties in Which Respondents Worked

Answer Choices	Responses	
Montgomery County, Pennsylvania	45.1%	23
Philadelphia County, Pennsylvania	43.1%	22
Delaware County, Pennsylvania	39.2%	20
Chester County, Pennsylvania	31.4%	16
Camden County, New Jersey	27.5%	14
Bucks County, Pennsylvania	27.5%	14
Burlington County, New Jersey	23.5%	12
Gloucester County, New Jersey	23.5%	12
Mercer County, New Jersey	21.6%	11

Source: DVRPC, 2019

The remainder of the survey was set up for ranking the importance of various factors. Respondents were asked to respond separately for residential and nonresidential development types.

Based on a preliminary discussion with the UrbanSim developers, the variables in the highest half of ranked variables were deemed important considerations. DVRPC used the survey results to identify the most readily available data for the most important issues, and sent those to UrbanSim for testing as a first cut of explanatory variables to improve the model. The survey results were also used to consider what additional data may be worth gathering for future model improvements.

The survey focused on factors that may not be directly included in an UrbanSim model by default. While the questions were structured to get a ranking of specific variables, it also provided open-ended questions to allow respondents to give input on important factors not listed. Zoning was identified as very important in many open-ended responses. UrbanSim already accounts for zoning by creating development capacities based on zoning codes for nearly all our 350 municipalities. As a result, zoning was not offered as an option in the survey. However, the first pass to identify regional development capacity did not factor in density bonuses afforded in overlay zoning districts. The survey responses were clear that this is important in many areas. DVRPC will further improve development capacities in places where overlays have significant implications.

Many respondents remarked that market forces can overcome obstacles to development. Market forces were not included as a factor precisely because of UrbanSim's ability to capture market forces.

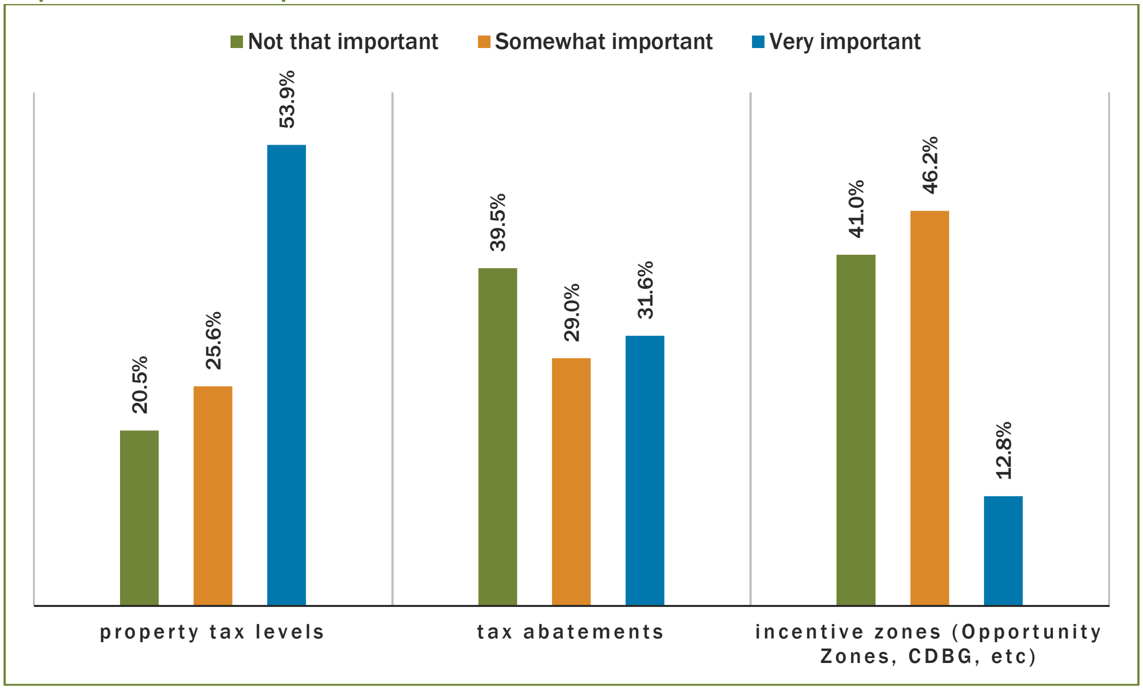
Respondents often used early open-ended questions to express the importance of factors (particularly regarding proximity/access-related) that were asked later in the survey.

It is possible that the survey results have some bias toward smart growth practices, as many were public sector planners and others were nonprofits interested in sustainability issues. One respondent was clearly focused on historic preservation, as their responses always focused on this topic, while no other respondent indicated its importance.

Policies, Incentives, Other Costs

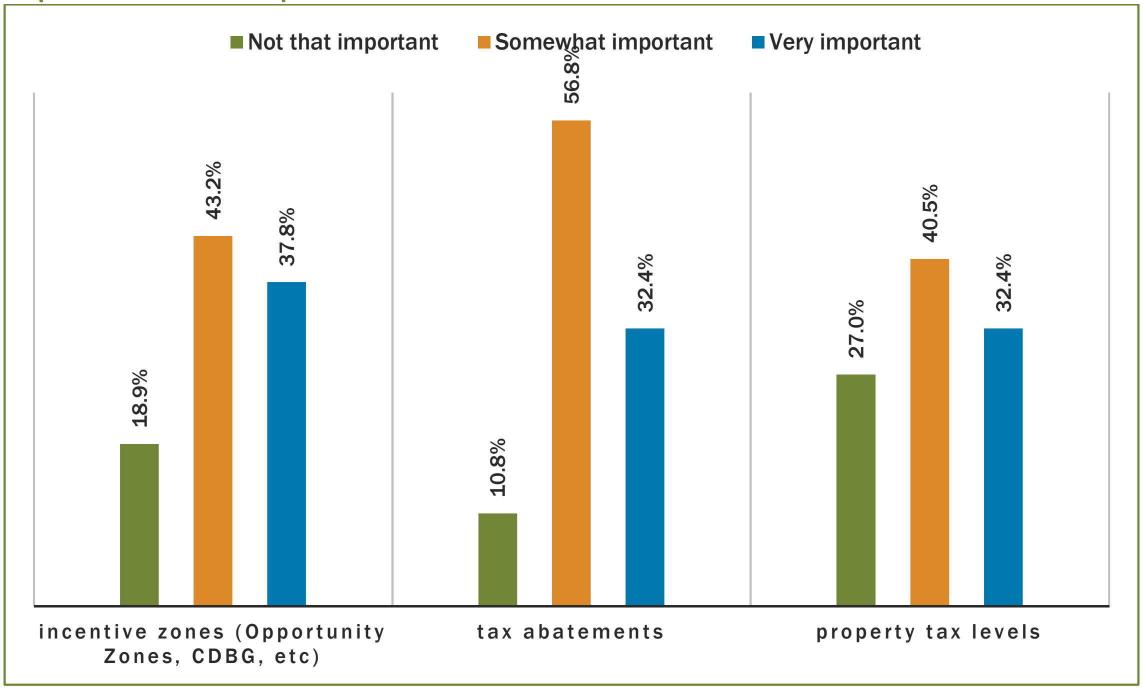
Figures E-1 and E-2 show the residential and nonresidential responses for the question, "In your experience, please rate the following based on importance for development to occur:"

Figure E-1: **Residential Responses to, "In your experience, please rate the following based on importance for development to occur:"**



Source: DVRPC, 2019

Figure E-2: Nonresidential Responses to, "In your experience, please rate the following based on importance for development to occur:"



Source: DVRPC, 2019

It's clear that between residential and nonresidential, all three of these factors play an important role. Staff recently gathered millage rates for the region's counties. We will explore with UrbanSim whether these results for most recent tax years will suffice or whether a 2010 base year data and years in between are needed. The open-ended follow up questions added some further nuance on what was important and added specificity on which incentive zones/programs are being used. Tables E-3 and E-4 present a quick summary of open-ended responses.

Table E-3: Responses to, "What incentive programs are important for residential development?"

Residential Summary	Count
Upzoning, Density Bonuses	13
Tax Abatements	10
Affordable housing tax credits	2
CDBG	2
Good (clear, speedy, reasonable application fees) process	2
Historic preservation tax credits	2
Opportunity Zones	2
Strong markets need no incentives	2
HOME FUNDS	1
Hope	1
LERTAs	1
LIHTC	1
PADCED (Elm Street Program)	1
Section 8	1

Source: DVRPC, 2019

Table E-4: Responses to, "What incentive programs are important for nonresidential development?"

Nonresidential Summary	Count
tax abatements	11
infrastructure support programs	4
LERTA	4
KOZ	4
Opportunity Zones	3
TRID	2
TIF	2
land write-downs	1
employee training assistance	1
land acquisition (land bank)	1
Urban Enterprises Initiatives	1
Rental stabilization programs for businesses	1
new market tax credit programs	1
NJ GRoW	1
NJEDA	1
P3s	1
BID	1
PADCED (Main Street Program)	1
Brownfield and greyfield remediation incentives	1
Philly Green Building credit (CB-5?)	1

Source: DVRPC, 2019

When asked “In your opinion, which municipalities/neighborhoods in the region are most attractive to development? Why?” Only a few respondents were specific about naming places. Most seemed to prefer denser urban areas or established boroughs, places with good transit access—which gets into accessibility/proximity section. But sometimes respondents contradicted each other. One said “Philadelphia-Center City highest concentration of urban amenities.” Another said, “various, NOT Philadelphia city?” Named places were:

- Camden, NJ (1)
- Chester County (1)
- Lower Bucks County (1)
- Lower Merion (1)
- Media (1)
- Montgomery County (1)
- Philadelphia (3)
- Philadelphia outer neighborhoods (1)
- Philadelphia-Center City (1)
- South Jersey (1)
- Trenton, NJ (1)

While the responses generally centered on proximity and access:

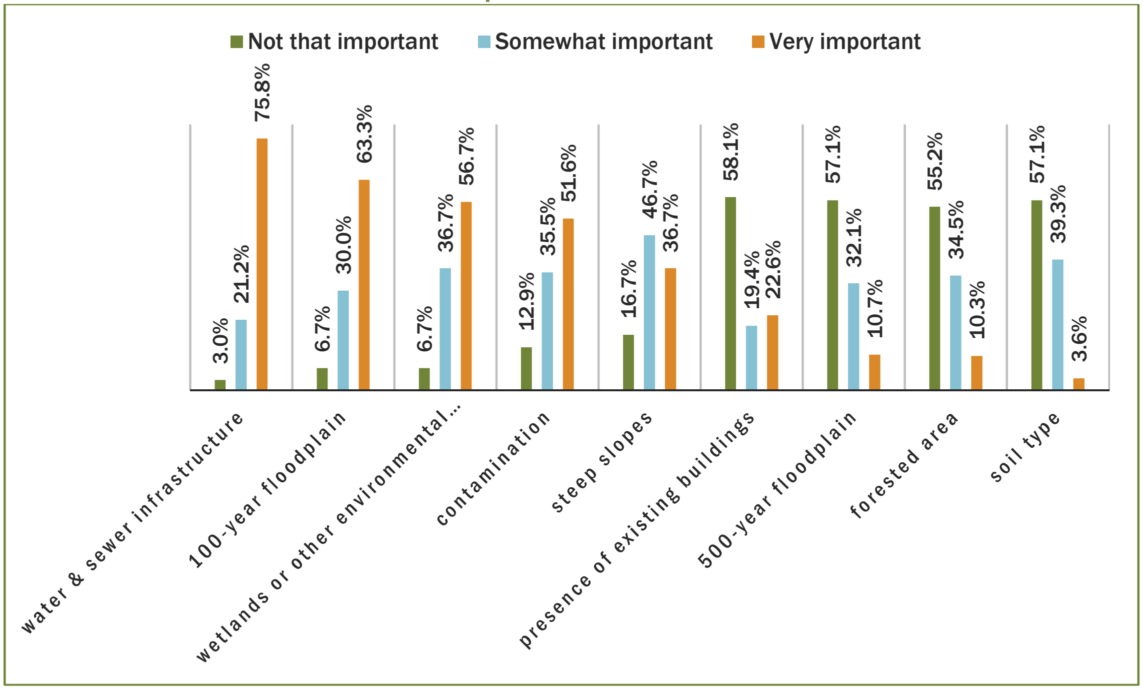
- Lower Merion was mentioned for multifamily zoning growth.
- Philadelphia was mentioned most frequently, though sometimes the place within was contradictory. Reasons were low land costs, taxes, ten-year tax abatement, and unions. One respondent said “Philadelphia has the most efficient least time-consuming entitlements process in the region, particularly for conforming development.”

There were other things mentioned that would be nearly impossible to collect good data on. For example: a clear, efficient development review process; or “Municipalities with progressive leadership interested in collaborative vision of the future.”

Site’s Physical Characteristics

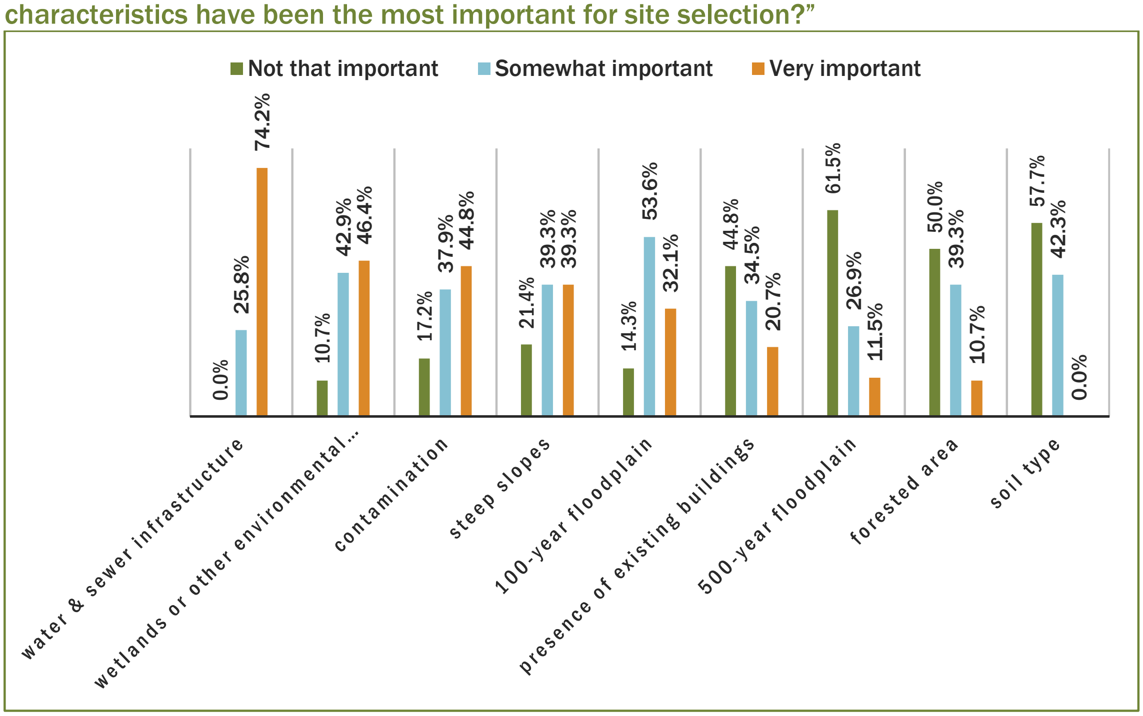
Figures E-3 and E-4 represent responses (sorted in order of most “Very Important” responses) for residential and nonresidential when asked: “Of the projects you have worked on, which physical characteristics have been the most important for site selection?”

Figure E-3: Residential Responses to, "Of the projects you have worked on, which physical characteristics have been the most important for site selection?"



Source: DVRPC, 2019

Figure E-4: Nonresidential Responses to, "Of the projects you have worked on, which physical characteristics have been the most important for site selection?"



Source: DVRPC, 2019

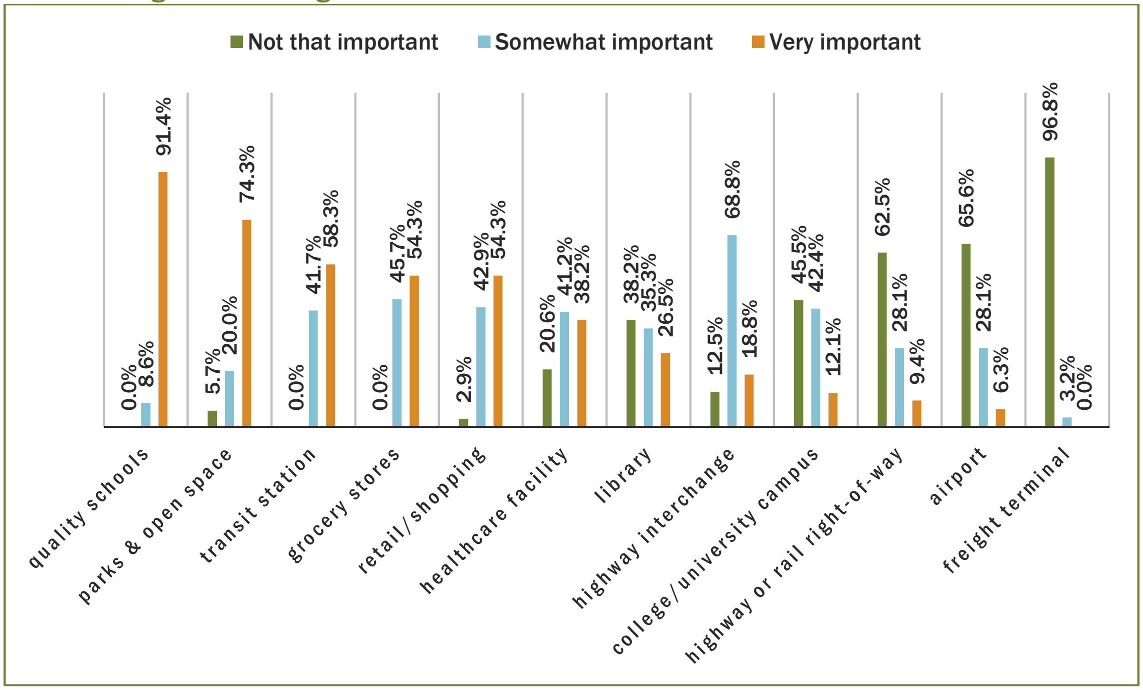
Residential and nonresidential responses for site's physical characteristics fell largely in line with each other. Further exploration is needed, but the many of these features are available in region-wide GIS layers or from many counties/states if not all. Contamination may be the most difficult and the "…or other environmental features" part of the response starting with "wetlands…" would need some work to define.

Open-ended responses for other physical features were almost all about site proximity/access.

Site's Proximity and Access

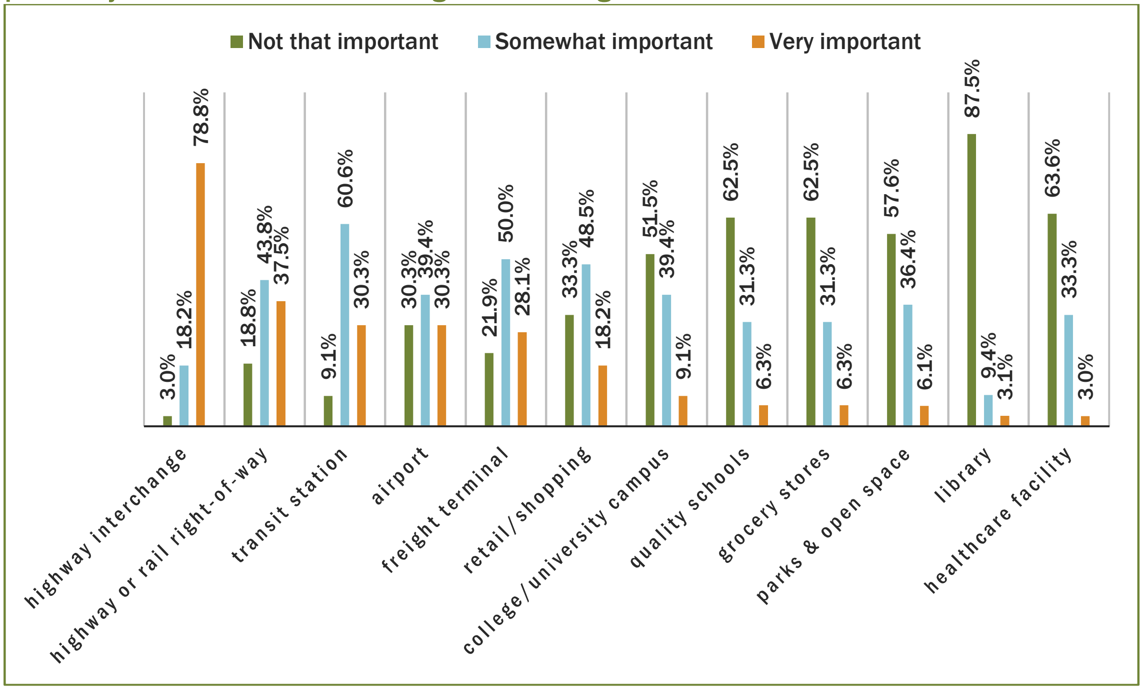
Figures E-5 and E-6 convey the responses (sorted in order of most "Very Important" responses) for residential and nonresidential when asked: "From your experience, how important are proximity or access to the following items during site selection?"

Figure E-5: Residential Responses to, "From your experience, how important are proximity or access to the following items during site selection?"



Source: DVRPC, 2019

Figure E-6: Figure 18: Nonresidential Responses to, "From your experience, how important are proximity or access to the following items during site selection?"



Source: DVRPC, 2019

Residential and nonresidential responses differed quite a bit for features proximate to either type of development. Like the physical characteristics of a site, many of these data items should be available through current DVRPC GIS resources, or by gathering features available from either state or our counties.

As expected, school quality is presumed to be a very important factor in residential development. However, this is problematic for forecasting. Since it is impossible to know which schools are likely to be most desirable in the future, DVRPC is very unlikely to incorporate school ratings into the land use model.

Open-ended responses to questions soliciting further proximity/access factors brought up items like commute time to employment centers and measures like the amount of employment accessible (or labor force accessible for nonresidential) within a certain timeframe. This is already a factor that is considered in the UrbanSim model. One comment, "Commuting time to Philadelphia or Wilmington," makes a great point about the accessibility to employment centers outside our region, which are not currently factored into UrbanSim. DVRPC can use travel time and employment/household counts from its travel model's extended region as an additional factor. This will help to better reflect areas of the region with high volumes of commuters with workplaces outside the region (Chester County has more commuters to New Castle County than to Philadelphia) that are considered as attractive locations to live. Likewise, areas within the region which pull a large number of workers from within and outside of the region are factors for nonresidential development.

"How wealthy the surrounding community is" was another verbatim response on other important proximity factors for nonresidential development. Presumably this is saying that a business (likely retail) may be attracted to locations proximate to prospective customers with higher disposable incomes. We can test this assumption relatively easily in UrbanSim.

The final question of the survey solicited and further comments to share with the survey team. None of these added new thoughts to the prioritization of factors. Many talked about macroeconomic factors or policies they felt that should be in place, which are not relevant to model development. Many comments reinforced statements previously expressed about zoning or market forces, etc. There were a couple of compliments on the survey itself, while one person suggested there were too many open-ended questions.

Appendix F

Glossary of Acronyms

Appendix F: Glossary of Acronyms

ACS – U.S. Census Bureau's American Community Survey

ADR - Analytical Data Report

BEA - Bureau of Economic Analysis

BLS - Bureau of Labor Statistics

BRAC - Base Realignment and Closure Commission

CTPP - Census Transportation Planning Products

D&B - Dun & Bradstreet, Inc.

DVRPC - Delaware Valley Regional Planning Commission

ELCM - Employment Location Choice Model

FY - Fiscal Year

GIS - Geographic information system

GQ - Group quarters

HLCM - Household Location Choice Model

HOA – Homeowners' association

IPF - Iterative proportional fitting

LEHD - Longitudinal Employer-Household Dynamics

LODES - LEHD Origin-Destination Employment Statistics

MOE - Margins of error

MPOs - Metropolitan planning organizations

NAICS - North American Industrial Classification System

NASJRB Willow Grove - Naval Air Station Joint Reserve Base Willow Grove

NETS - National Establishment Time-Series

PCPC - Philadelphia City Planning Commission

PEP – U.S. Census Bureau's Population Estimates Program

PUMA - Public Use Microdata Areas

PUMS - Public Use Microdata Sample

RDPLCM - Residential Development Project Location Choice Model

REPM - Real Estate Pricing Model

RTC - Regional Technical Committee

SLUAC - Socioeconomic and Land Use Analytics Committee

TAZ (or zone) - Travel analysis zone

TIP - Transportation Improvement Program

Population and Employment Forecasts 2015–2050

Publication Number: ADR21014

Date Published: January 2023

Geographic Area Covered:

DVRPC's nine-county region, including Burlington, Camden, Gloucester, and Mercer counties in New Jersey, and Bucks, Chester, Delaware, Montgomery, and Philadelphia counties in Pennsylvania.

Key Words:

population, population forecasts, employment, employment forecast, National Establishments Time-Series database, NETS, development, land use model, UrbanSim, *Connections 2050*, long-range plan.

Abstract:

This report presents the Delaware Valley Regional Planning Commission's (DVRPC's) adopted 2050 county- and municipal-level population and employment forecasts and describes the method used to develop them. Population and employment forecasts are a critical component of long-range land use and transportation planning. As a part of DVRPC's long-range planning activities, the Commission is required to maintain forecasts with at least a 20-year horizon, or to the horizon year of the long-range plan. DVRPC last adopted forecasts through the year 2045 in 2016.

Referenced as the 2050 v1.0 forecasts, as the first to use that horizon year, the population and employment totals were formally adopted by the DVRPC Board on June 24, 2021, and serve as the basis for DVRPC planning and travel modeling activities.

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