Piedmont Housing Alliance Data Analysis

2023-06-27

```
# Load data management and analysis tools

library(tidyverse)
library(tidycensus)
library(readxl)
library(janitor)
library(lubridate)

# Load spatial analysis tools

library(tidygeocoder)
library(sf)
library(tigris)
library(mapview)

# Load data visualization tools

library(hdatools)
library(scales)
library(ggtext)
library(ggridges)
library(kableExtra)
library(reactable)
library(patchwork)
library(formattable)

# Set defaults

setwd("~/repos/piedmont")
```

```
today <- Sys.Date()
```

About

Piedmont Housing Alliance (PHA) is a 501(c)3 nonprofit organization that provides housing services to clients in the Charlottesville, Virginia region. In 2022, PHA received a Tier III Capacity Building Program Enhancement Grant from Virginia Housing to evaluate and improve their programs aimed at helping first-time homebuyers.

> **How PHA helps first-time homebuyers**
>
> PHA offers two programs to help buyers earning less than 80% of Area Median Income (AMI) purchase their first home.
>
> 1. The **Down Payment Loan** (DPL) program combines funding from several different sources to provide buyers with additional assistance to increase their total down payment and cover closing costs. This allows buyer to more easily afford homes at prices they would otherwise be unable to afford.
> 2. PHA administers the **Sponsoring Partnerships & Revitalizing Communities** (SPARC) program, which lowers a buyer's mortgage interest rate by 1.00%. SPARC funds are allocated by Virginia Housing and help buyers save thousands of dollars over the life of their loan.

PHA seeks a deeper understanding of these two programs' outcomes and impacts, particularly in terms of racial equity and wealth-building. This document was prepared by HDAdvisors to develop methods for evaluating the program using internal and external data.

Goals

The primary goal of this analysis is a preliminary evaluation of the DPL and SPARC programs' current abilities to support buyers who are more likely to be at a systemic disadvantage because of unjust lending practices and other discriminatory efforts.

The secondary goal is to provide PHA staff with reproducible methods for collecting, preparing, and analyzing the data necessary for this evaluation. This will allow PHA to regularly track and monitor these programs without outside assistance.

> **Why this matters**
>
> This analysis will be helpful for PHA in three important ways:
>
> 1. To proactively assess whether the program fulfills all applicable fair housing requirements,
> 2. To provide staff with a thorough understanding of program outcomes for stronger grant applications, and
> 3. To further PHA's existing Diversity, Equity, and Inclusion (DEI) efforts.

Guiding questions

The following questions help determine (1) what kind of data is needed, and (2) how that data should be analyzed.

- How do PHA's clients vary by race, ethnicity, and income compared to the region as a whole?
- Do the levels of assistance vary significantly by race, ethnicity, and income?
- Are there noticeable migration patterns for clients purchasing their first home?
- How do the homes purchased by clients compare to similar homes in that neighborhood?
- How much home equity have past clients gained? How similar are these gains across race, ethnicity, and neighborhoods?

Data assembly

This section outlines each metric necessary for analysis, along with methods for collecting and cleaning the appropriate data.

Program and client data

PHA provided data on DPL and SPARC clients from FY 2018 through FY 2023.

This data includes attributes about each client household, including:

- Total annual income
- Area median income (AMI)
- Race and ethnicity (optional)
- Number of persons

- Street address (at time of application)

It also includes DPL-specific program data, including:

- Number of loans provided
- Total amount of DPL assistance
- Funding sources used for each loan
- Source(s) and amount of non-DPL assistance

Information on the homes purchased by clients include:

- Street address
- Sales price
- Appraised value
- Closing costs and other prepaids

Information about clients' mortgages are also provided:

- Lending institution
- Mortgage product
- Mortgage amount
- Interest rate
- Original interest rate (SPARC only)
- Closing date

The full dataset includes multiple other fields that are not necessary or relevant to this analysis.

Step 1: Import data

```
# Import list of DPL clients and clean column names

clients_dpl_raw <- read_xlsx("data/raw/clients.xlsx",
                             sheet = "Down Payment Loan") |>
  clean_names()


# Import list of SPARC clients and clean column names

clients_sparc_raw <- read_xlsx("data/raw/clients.xlsx",
                             sheet = "SPARC") |>
  clean_names()
```

Step 2: Clean up and fix data

```r
# Clean up DPL data

clients_dpl <- clients_dpl_raw |>

  # Drop rows that do not have client records

  drop_na(contract_date) |>

  # Remove columns with personal information or unnecessary data

  select(!c(fha_case_number, ami_approval_date, client_intake_date,
            client_last_name, client_first_name, counselor,
            service_type, client_employer, employer_msa,
            property_msa, status, loan_officer, client_msa,
            client_email_address, phone_number
            )) |>

  # Rename certain columns to more helpful descriptions

  rename(mortgage_product = x1st_mortgage_product,
         mortgage_amount = x1st_mortgage_amount,
         pha_loans_n = number_of_pha_loans,
         pha_loans_amount = of_pha_loans,
         pha_loan_source = source_of_pha_loan
         ) |>

  # Create new unique DPL client ID column

  mutate(id_dpl = str_c("DPL", str_pad(row_number(), 3, pad = "0")),
         .before = 1) |>

  # Clean up original client_number column

  mutate(client_number = str_remove_all(client_number, "\\.0")) |>

  # Change "Unknown" values to NA in appraised_value

  mutate(appraised_value = as.numeric(na_if(appraised_value, "Unknown"))) |>

  # Clean up lending_institution names
```

```
mutate(lending_institution = case_when(
  str_detect(lending_institution, "Coast") ~ "Atlantic Coast Mortgage",
  str_detect(lending_institution, "Fulton") ~ "Fulton Mortgage",
  str_detect(lending_institution, "Charlottesville") ~ "Habitat for Humanity of Greater
  str_detect(lending_institution, regex("first", ignore_case = T)) ~ "Towne First Mortga
  str_detect(lending_institution, "USDA") ~ "USDA",
  str_detect(lending_institution, "Waterstone") ~ "Waterstone Mortgage Corporation",
  lending_institution == "Towne Bank Mortgage" ~ "TowneBank Mortgage",
  TRUE ~ lending_institution
)) |>

# Clean up mortgage_product names

mutate(mortgage_product = case_when(
  str_detect(mortgage_product, "502|USDA|RHS") ~ "502 Direct Loan",
  mortgage_product == "Coventional" ~ "Conventional",
  str_detect(mortgage_product, "VHDA FHA|VHDA - HFA") ~ "VHDA - FHA",
  TRUE ~ mortgage_product
)) |>

# Change '$-' values in other_assistance_amount to NA

mutate(other_assistance_amount = as.numeric(na_if(other_assistance_amount, "$-"))) |>

# Create column for single or multiple race; clean up race names

mutate(multirace = case_when(
    str_detect(race, "Multi") ~ "Multiple",
    TRUE ~ "Single"),
  .before = race) |>

mutate(race = case_when(
  str_detect(race, "and White") ~ "Black and White",
  str_detect(race, "Other") ~ "Other races",
  str_detect(race, "Asian") ~ "Asian",
  str_detect(race, "Single Race - Black") ~ "Black",
  TRUE ~ "White"
)) |>

# Simplify rural_area_status and english_proficiency columns
```

```
  mutate(rural_area_status = case_when(
    str_detect(rural_area_status, "lives") ~ "Rural",
    TRUE ~ "Not rural"
  )) |>

  mutate(english_proficiency = case_when(
    str_detect(english_proficiency, "is not") ~ "Not proficient",
    TRUE ~ "Proficient"
  ))
```

```
# Clean up SPARC data

clients_sparc <- clients_sparc_raw |>

  # Remove columns with personal information or unnecessary data

  select(!c(last_name, first_name, client,
            lenders_name, x20)) |>

  # Rename certain columns to match DPL data

  rename(sale_price = sales_price,
         mortgage_amount = base_loan_amount,
         household_annual_income = borrower_s_income,
         household_size = number_in_hh,
         locality = msa,
         mortgage_product = loan_product,
         lending_institution = lending_company
         ) |>

  # Change client_number column to string

  mutate(client_number = as.character(client_number)) |>

  # Create new unique SPARC client ID column

  mutate(id_sparc = str_c("SPC", str_pad(row_number(), 3, pad = "0")),
         .before = 1) |>

  # Fix interest_rate values
```

```
mutate(interest_rate = case_when(
  interest_rate > 1 ~ interest_rate/100,
  TRUE ~ interest_rate
)) |>

# Create mortgage_notes column for specific loan info

mutate(mortgage_notes = case_when(
  str_detect(mortgage_product, "No MI") ~ "No mortgage insurance",
  str_detect(mortgage_product, "Reduced") ~ "Reduced mortgage insurance",
  str_detect(mortgage_product, "Second Plus") ~ "Second Plus",
  TRUE ~ NA_character_),
  .after = mortgage_product
  ) |>

# Clean up mortgage_product names to match DPL data

mutate(mortgage_product = case_when(
  str_detect(mortgage_product, regex("Conventional", ignore_case = T)) ~ "Conventional",
  str_detect(mortgage_product, regex("RHS", ignore_case = T)) ~ "502 Direct Loan",
  str_detect(mortgage_product, regex("FHA", ignore_case = T)) ~ "FHA",
  is.na(mortgage_product) ~ "Unknown",
  TRUE ~ mortgage_product
)) |>

# Clean up lending_institution names to match DPL data

mutate(lending_institution = case_when(
  str_detect(lending_institution, "C&F") ~ "C&F Mortgage Corporation",
  str_detect(lending_institution, "Waterstone") ~ "Waterstone Mortgage Corporation",
  is.na(lending_institution) ~ "Unknown",
  TRUE ~ lending_institution
)) |>

# Clean up yes/no columns

mutate(received_cd = case_when(
  str_detect(received_cd, "YES|Yes|yes") ~ "Yes",
  received_cd == "no" ~ "No",
  received_cd == "N/A" ~ NA_character_,
  TRUE ~ NA_character_
```

```
  )) |>

  mutate(in_ors = case_when(
    str_detect(in_ors, "No -") ~ "No",
    TRUE ~ in_ors
  ))
```

Step 3: Join DPL and SPARC client data

Some clients use both the DPL and SPARC programs to purchase their home. For now, these clients were identified by manually cross-referencing names and other fields. To join the data, the DPL `client_number` values were assigned to the respective client records in the SPARC data.

In the future, PHA should maintain a single client dataset that can differentiate between DPL-only, SPARC-only, and "double-dipping" clients. Specific recommendations will be detailed at the end of this document.

```
# Create full join using client_number

clients_all <- clients_dpl |>
  full_join(clients_sparc, by = "client_number", na_matches = "never",
            suffix = c("_dpl", "_spc")) |>

  # Reorder columns to place duplicate fields together

  select(2, 1, 46, 3, 4, 47, 5, 52, 6, 7, 53, 8, 9,
         10, 11, 12, 13, 14, 50, 15, 16, 17, 59, 18,
         55, 19, 51, 20, 49, 48, 50, 21, 22, 23, 24,
         25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35,
         36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 54,
         56, 57, 60, 61
         ) |>

  # Create column to show whether client uses one or both programs

  mutate(program = case_when(
      !is.na(id_dpl) & !is.na(id_sparc) ~ "Both",
      !is.na(id_dpl) & is.na(id_sparc) ~ "DPL",
      TRUE ~ "SPARC"),
    .before = 1) |>

  # Create universal client ID column
```

```
  mutate(id_pha = str_c("PHA", str_pad(row_number(), 3, pad = "0")),
         .before = 1)
```

Step 4: View data

Cleaned and joined client data are shown in the table below.

```
reactable(clients_all,
          defaultPageSize = 5,
          defaultColDef = colDef(minWidth = 150),
          compact = TRUE,
          striped = TRUE,
          wrap = FALSE)
```

id_pha	program	client_number	id_dpl	id_sparc	contract_date	close_date_dpl	close_date_spc	household_annua…	household_annua…
PHA001	Both	4305081	DPL001	SPC002	2022-05-24T00:00…	2022-07-26T00:00…	2022-07-27T00:00…	59600.08	66000.08
PHA002	DPL	4658207	DPL002		2022-06-25T00:00…	2022-08-02T00:00…		58323.44	
PHA003	DPL	4650788	DPL003		2021-07-21T00:00…	2021-08-21T00:00…		55016	
PHA004	Both	4721465	DPL004	SPC022	2021-06-28T00:00…	2021-08-21T00:00…	2021-08-27T00:00…	35459.84	33234

1–5 of 131 rows

Previous 1 2 3 4 5 ... 27 Next

Where there were duplicate fields from each dataset, the `_dpl` and `_spc` suffixes were added to the end of column names, respective to their source. For example, the close date data from the DPL records are retained as the `close_date_dpl` column, while the close dates from the SPARC data are `close_date_spc`.

⚠ Data integrity issues

Both the DPL and SPARC datasets were found to have data integrity issues that PHA should resolve in the future.

- Mortgage product fields included both "RHS" (Rural Housing Service), "USDA", and "502" values. For now, these are all assumed to be "502 Direct Loans".
- Overlapping fields from the DPL and SPARC datasets do not always reconcile for the clients who used both programs. For example, the specific close dates and household income values are often slightly different—but should, in theory, be identical.
- The SPARC client records are missing many values in the closing date, interest rate, household income, household size, and lender columns.
- Some DPL clients were noted as receiving SPARC in the `other_assistance` column. However, two of clients were *not* found in the SPARC data.

Regional and neighborhood profiles

💡 Why this is needed

Demographic and socioeconomic data will help establish the baseline characteristics of population groups that PHA seeks to compare with its clients. For example, how closely does the client pool match the average racial and ethnic makeup across the region?

Two datasets will be used to create summary profiles of the geographies PHA will use as reference for its clients' characteristics. Both are from the U.S. Census Bureau:

- 2020 Decennial Census
- American Community Survey (5-year estimates)

ℹ Note

As of June 2023, the latest ACS data available are the 2017-2021 5-year estimates.

The fields to collect from this data include:

- Race and ethnicity of population
- Average household incomes

- Homeownership rates

Step 1: Race and ethnicity data from 2020 Census

```
# Get variables for 2020 Census PL-94171 Redistricting dataset

pl_vars <- load_variables(2020, "pl", cache = TRUE)

# Find and select race and ethnicity variables

race_vars <- pl_vars |>
  filter(name %in% c(
    "P1_003N", # White
    "P1_004N", # Black
    "P1_005N", # American Indian and Alaska Native
    "P1_006N", # Asian
    "P1_007N", # Native Hawaiian and Other Pacific Islander
    "P1_008N", # Some other race
    "P1_009N", # Two or more races
    "P2_002N", # Total Hispanic or Latino
    "P2_003N"  # Total not Hispanic or Latino
  )) |>

  # Rename race and ethnicity groups

  mutate(label = case_when(
    name == "P1_003N" ~ "White",
    name == "P1_004N" ~ "Black",
    name == "P1_005N" ~ "Another race",
    name == "P1_006N" ~ "Asian",
    name == "P1_007N" ~ "Another race",
    name == "P1_008N" ~ "Another race",
    name == "P1_009N" ~ "Multiracial",
    name == "P2_002N" ~ "Hispanic or Latino",
    name == "P2_003N" ~ "Not Hispanic or Latino",
  )) |>

  # Add race/ethnicity label

  mutate(category = case_when(
      str_detect(name, "P1") ~ "Race",
      TRUE ~ "Ethnicity"),
```

```
    .after = 1
  ) |>

  # Drop concept column (unneeded)

  select(-concept)

# Import 2020 Census race and ethnicity data for Charlottesville City

cv_race_raw <- get_decennial(
  geography = "county",
  variables = race_vars$name,
  year = 2020,
  sumfile = "pl",
  state = "VA",
  county = "Charlottesville city",
  cache_table = TRUE
)
```

```
# Join race and ethnicity labels

cv_race <- cv_race_raw |>
  left_join(race_vars, by = c("variable" = "name")) |>

  # Sum "Another race" values into one row

  group_by(category, label) |>
  summarise(value = sum(value)) |>

  # Add percent column

  group_by(category) |>
  mutate(pct = value/sum(value)) |>
  ungroup()

# Generate table

cv_race |>
  arrange(desc(value), .by_group = TRUE) |>
  kable() |>
  kableExtra::kable_styling(
```

category	label	value	pct
Ethnicity	Not Hispanic or Latino	43346	0.9311108
Race	White	30344	0.6518162
Race	Black	7122	0.1529869
Race	Asian	4083	0.0877065
Race	Multiracial	3583	0.0769660
Ethnicity	Hispanic or Latino	3207	0.0688892
Race	Another race	1421	0.0305243

```
    bootstrap_options = c("striped", "hover", "condensed", "responsive")
  )
```

Step 2: Household income data from ACS

```
# Get variables for Table B25118: Tenure by Household Income

b25118_vars <- load_variables(2021, "acs5", cache = TRUE) |>
  filter(str_sub(name, end = 6) %in% "B25118")

# Clean variables

inc_vars <- b25118_vars |>
  separate(label, c("est", "total", "tenure", "income"), sep = "!!") |>
  select(1, 4, 5) |>
  drop_na() |>
  mutate(tenure = str_remove_all(tenure, " occupied:"),
         tenure = str_replace_all(tenure, "Owner", "Homeowner"))

# Import 2021 ACS estimates

b25118_raw <- get_acs(
  geography = "county",
  variables = inc_vars$name,
  year = 2021,
  county = "Charlottesville city",
  state = "VA",
  cache_table = TRUE
)
```

```r
# Join variables to data

cv_income <- b25118_raw |>
  left_join(inc_vars, by = c("variable" = "name")) |>

  # Remove unnecessary columns and rearrange

  select(6, 7, 4) |>

  # Collapse into fewer income categories

  mutate(income = case_when(
    income == "Less than $5,000" ~ "Less than $35,000",
    income == "$5,000 to $9,999" ~ "Less than $35,000",
    income == "$10,000 to $14,999" ~ "Less than $35,000",
    income == "$15,000 to $19,999" ~ "Less than $35,000",
    income == "$20,000 to $24,999" ~ "Less than $35,000",
    income == "$25,000 to $34,999" ~ "Less than $35,000",
    income == "$100,000 to $149,999" ~ "$100,000 or more",
    income == "$150,000 or more" ~ "$100,000 or more",
    TRUE ~ income
  )) |>
  group_by(tenure, income) |>
  summarise(estimate = sum(estimate))

# Generate table

cv_income |>
  ungroup() |>
  mutate(income = fct_relevel(income, "Less than $35,000", "$35,000 to $49,999",
                              "$50,000 to $74,999", "$75,000 to $99,999",
                              "$100,000 or more")) |>
  arrange(income) |>
  kable() |>
  kableExtra::kable_styling(
    bootstrap_options = c("striped", "hover", "condensed", "responsive")
  )
```

Step 3: Homeownership data from ACS

```r
# tbd
```

tenure	income	estimate
Homeowner	Less than $35,000	883
Renter	Less than $35,000	5140
Homeowner	$35,000 to $49,999	764
Renter	$35,000 to $49,999	1234
Homeowner	$50,000 to $74,999	861
Renter	$50,000 to $74,999	1809
Homeowner	$75,000 to $99,999	1171
Renter	$75,000 to $99,999	985
Homeowner	$100,000 or more	4300
Renter	$100,000 or more	2165

```
# tbd
```

Mortgage applications and activity

> **Why this is needed**
>
> Along with comparing client characteristics with the region or a neighborhood as a whole, we can compare their mortgages to overall lending activity in the community over time. This will allow PHA to benchmark its buyer assistance efforts to home loan trends across the region.

This information is available from the Home Mortgage Disclosure Act (HMDA) data from the Consumer Financial Protection Bureau. HMDA data include loan-level information on buyer demographics, loan attributes, and property characteristics. Entries for buyers whose applications were eventually withdrawn or denied are also included.

> **Note**
>
> As of June 2023, the latest HMDA data available is for 2021.

The fields to collect from this data include:

- Buyer race and ethnicity
- Buyer county and census tract
- Loan type (conventional, FHA, VA, or USDA)
- Action taken (loan originated, application denied or withdrawn)
- Loan amount
- Interest rate

- Property value
- Occupancy type (principal residence only)
- Buyer gross annual income
- Debt-to-income ratio

> **Future work**
>
> This data was not collected within the scope of the original project. Analysis with this data could be completed as a future update.

Home values

> **Why this is needed**
>
> Detailed data on home sales and values are necessary to make estimates about the total home equity gained (or lost) by PHA buyers and other homeowners in the community. This property-level data will help PHA assess its programs' abilities to support wealth-building among clients.

Real estate assessments

Localities in PHA's service area regularly assess property values to calculate the total real estate taxes to be paid by each property owner. Properties are reassessed to better match taxable values with potential market values, which can change significantly over time.

Despite these updates, local assessments can often lag behind current market trends, so they are not the most accurate indicator of the actual market value of a home if it were sold. Still, assessment data are consistent and publicly available for all parcels in a locality. This creates a useful longitudinal dataset.

For this preliminary analysis, only assessment data from the City of Charlottesville will be used.

The fields to collect from this data include:

- Parcel number
- Street number and name
- Bedrooms and bathrooms
- Finished square footage
- Total assessed value

```r
# Load in multi-year assessment data

cv_assess <- read_csv("data/raw/Real_Estate_(All_Assessments).csv") |>

  # Filter tax years 2017 and later

  filter(TaxYear > 2016) |>

  # Keep only relevant fields

  select(ParcelNumber, TotalValue, TaxYear)
```

```r
# Load in detailed residential property data

cv_residential <- read_csv("data/raw/Real_Estate_(Residential_Details).csv") |>

  # Filter for single-family types only

  filter(str_detect(UseCode, "Single Family")) |>

  # Keep only relevant fields

  select(ParcelNumber, StreetNumber, StreetName, Bedrooms, HalfBathrooms,
         FullBathrooms, SqFt = SquareFootageFinishedLiving)

# Load shapefile of parcels

cv_parcels <- st_read("data/shp/Parcel_Area_Details.shp") |>

  # Project into Virginia State Plane South

  st_transform(4502) |>

  # Fix column name

  select(ParcelNumber = ParcelNumb) |>

  # Join to detailed residential property data

  right_join(cv_residential, by = "ParcelNumber")
```

```
# Save data

write_rds(cv_parcels, "data/cv_parcels.rds")
```

MLS sales

Actual recorded home sales are the most accurate way to determine residential property values. For arms-length transactions, sales prices reflect the actual market value of each home. These records are therefore the ideal source to best determine home equity changes among homeowners.

PHA is able to provide data exported from the multiple listing service (MLS) operated by the Charlottesville Area Association of REALTORS® (CAAR). The MLS platform includes all real estate listings from agents in the region and is dynamically updated as listings are added, updated, or closed.

For this preliminary analysis, PHA has provided data on all sold single-family homes in the City of Charlottesville from September 2022 through November 22, 2022.

Fields included in this exports include:

- Property address
- Days on market
- List price
- Closed date
- Bedrooms and bathrooms
- Finished square footage

```
# Load in records exported from MLS and clean column names

mls <- read_csv("data/raw/Default_MLS_Defined_Spreadsheet.csv") |>
  clean_names() |>

  # Keep only relevant fields

  select(address, city, closed_date, number_beds, number_baths, total_sq_ft, list_price)

# Add state field and geocode addresses

mls_geocode <- mls |>
  mutate(state = "VA", .before = 3) |>
  geocode(street = address,
```

```
          state = state,
          city = city,
          method = "geocodio",
          lat = lat,
          long = long) |>

  # Drop records that did not match

  drop_na(lat) |>

  # Specify WGS 1984 coordinate system for lat/long data

  st_as_sf(coords = c("long", "lat"),
           remove = FALSE,
           crs = 4326) |>

  # Project into Virginia State Plane South

  st_transform(4502)

# Save data

write_rds(mls_geocode, "data/mls_geocode.rds")
```

Public sales records

The City of Charlottesville also maintains a public record of real estate transactions on their open data portal. This data is accessed and used in the Section **??** section.

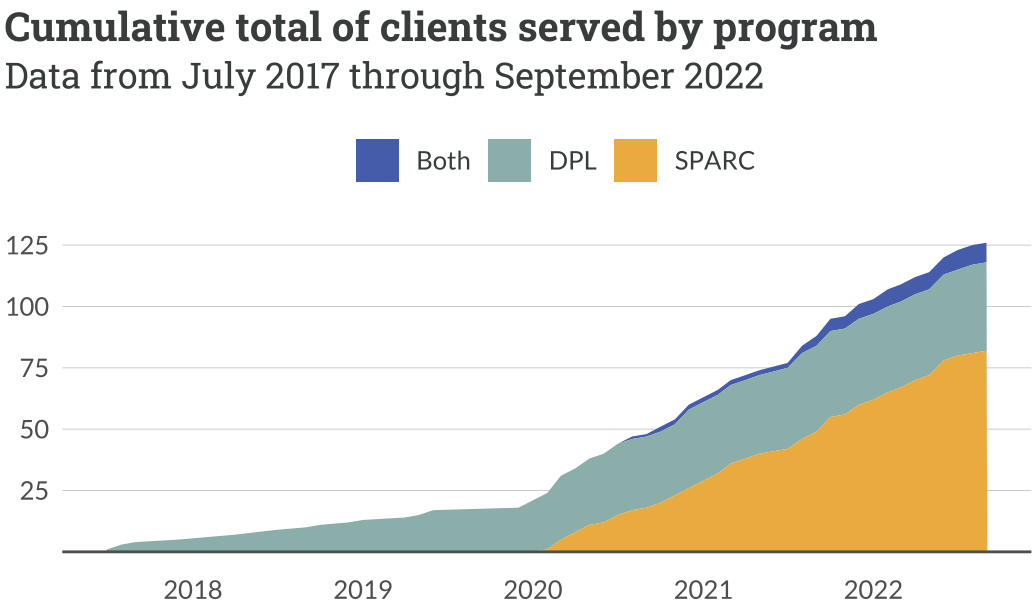
Analysis

Clients served by program

From July 2017 through September 2022, PHA served a total of 131 households with its DPL and SPARC programs.

```
# Cumulative total served by program
```

```r
clients_total <- clients_all |>
  select(program, close_date_dpl, close_date_spc) |>

  # Collapse close dates into one column
  # Assume DPL close date is correct when SPARC date differs

  mutate(close_date = case_when(
    !is.na(close_date_dpl) ~ close_date_dpl,
    TRUE ~ close_date_spc
  ))

# Summarise clients by month

clients_cum <- clients_total |>
  drop_na(close_date) |>
  count(program, month = floor_date(close_date, "month")) |>
  ungroup() |>
  complete(program, month, fill = list(n = 0)) |>

  # Cumulative sum by program

  group_by(program) |>
  mutate(cum_sum = cumsum(n))

# Create plot

ggplot(clients_cum, aes(x = month, y = cum_sum, fill = program)) +
  geom_area() +
  scale_y_continuous(breaks = c(25,50,75,100,125)) +
  scale_fill_hda() +
  labs(title = "Cumulative total of clients served by program",
       subtitle = "Data from July 2017 through September 2022",
       caption = "**Note:** Four records without close dates are omitted.") +
  theme_hda() +
  add_zero_line("y") +
  theme(
    legend.position = "top"
  )
```

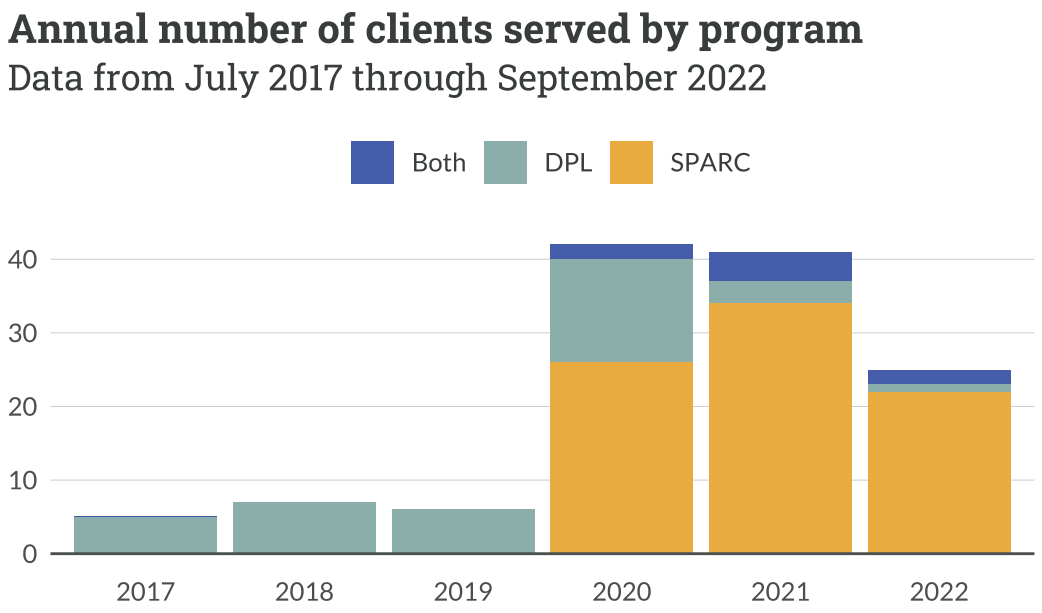


Note: Four records without close dates are omitted.

PHA served DPL-only clients from 2017 through 2019, averaging fewer than ten annually. In 2020, PHA began offering SPARC, which has been used by more than 25 clients annually since. Several clients have used both DPL and SPARC assistance each year since 2020.

```
# Summarise data by program and year

clients_annual <- clients_total |>
  drop_na(close_date) |>
  count(program, year = floor_date(close_date, "year")) |>
  ungroup() |>
  complete(program, year, fill = list(n = 0)) |>
  mutate(year = format(year, "%Y"))

# Create plot

ggplot(clients_annual, aes(x = year, y = n, fill = program)) +
  geom_col(position = "stack") +
  scale_fill_hda() +
  labs(title = "Annual number of clients served by program",
       subtitle = "Data from July 2017 through September 2022",
       caption = "**Note:** Four records without close dates are omitted.") +
  theme_hda() +
```

```
  add_zero_line("y") +
  theme(
    legend.position = "top"
  )
```

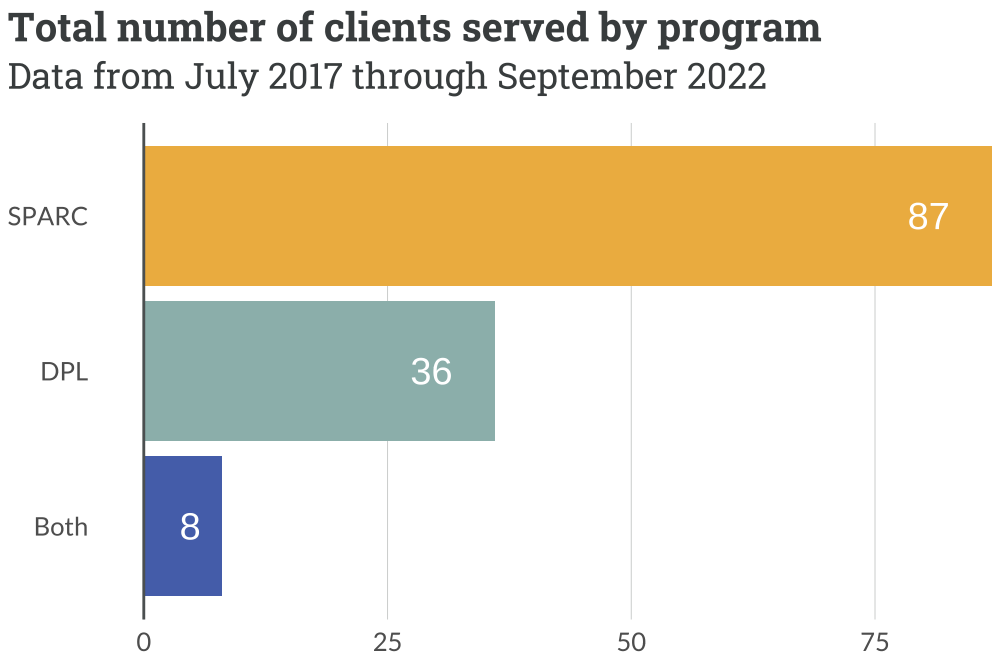


Note: Four records without close dates are omitted.

In total, two-thirds (66 percent) of all clients used SPARC only. About one quarter (27 percent) used DPL only, and just eight clients (6 percent) took advantage of both.

```
# Summarise data by program

clients_program <- clients_total |>
  count(program)

# Create plot

ggplot(clients_program, aes(y = reorder(program, n), x = n, fill = program, label = n)) +
  geom_col() +
  geom_text(hjust = 2,
            color = "white",
            size = 5) +
  scale_fill_hda() +
```

```
labs(title = "Total number of clients served by program",
     subtitle = "Data from July 2017 through September 2022") +
theme_hda() +
add_zero_line("x") +
flip_gridlines()
```



Profile of clients

> **Note**
>
> Race and ethnicity data is only available for clients who used the DPL program.

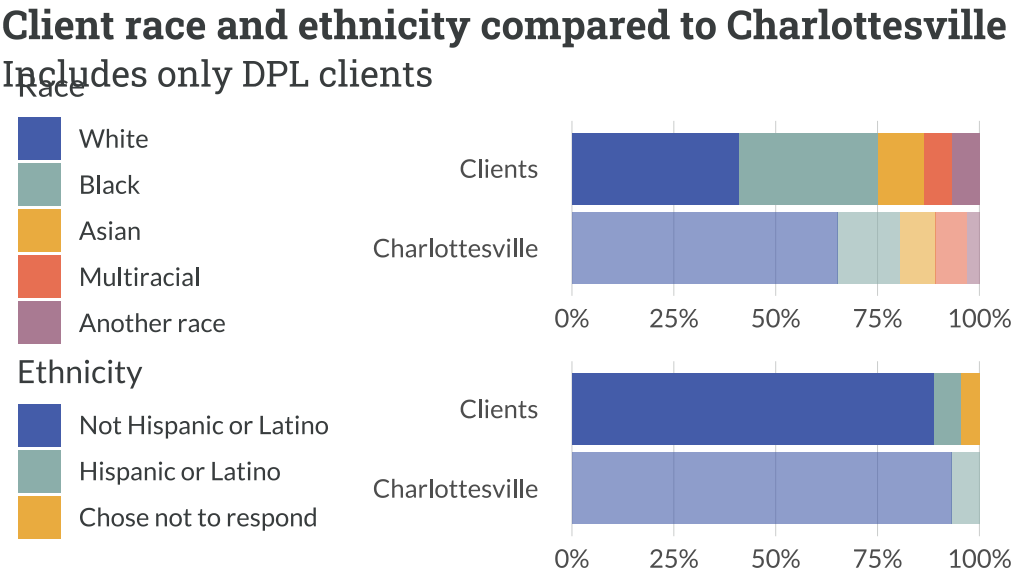
Among the 44 clients who used the DPL program, most were white (41 percent) or Black (34 percent). Another 11 percent were Asian, with the remainder being multiracial or of another race. This is a more diverse pattern than Charlottesville as a whole, where 65 percent of residents are white, while only 15 percent of residents are Black, and 9 percent are Asian.

The share of DPL clients who are Hispanic or Latino is about 7 percent, which aligns very closely with the overall population of Charlottesville.

```r
# Summarise clients by race

clients_race <- clients_all |>
  count(race) |>
  drop_na() |>
  ungroup() |>

  # Add percent column

  mutate(pct = n/sum(n)) |>

  # Add source and category columns

  mutate(source = "Clients",
         category = "Race",
         .before = 1) |>

  # Update race labels and column names to match ACS data

  mutate(race = case_when(
    race == "Black and White" ~ "Multiracial",
    race == "Other races" ~ "Another race",
    TRUE ~ race)) |>
  rename(label = race,
         value = n)

# Same as above for ethnicity

clients_ethnicity <- clients_all |>
  count(ethnicity) |>
  drop_na() |>
  ungroup() |>

  # Add percent column

  mutate(pct = n/sum(n)) |>

  # Add source and category columns

  mutate(source = "Clients",
         category = "Ethnicity",
```

```
          .before = 1) |>

  # Update race labels and column names to match ACS data

  mutate(ethnicity = case_when(
    ethnicity == "Hispanic" ~ "Hispanic or Latino",
    ethnicity == "Not Hispanic" ~ "Not Hispanic or Latino",
    TRUE ~ ethnicity)) |>
  rename(label = ethnicity,
         value = n)

# Add client data to ACS data

race_join <- cv_race |>
  mutate(source = "Charlottesville", .before = 1) |>
  bind_rows(clients_race, clients_ethnicity)

race_plot <- race_join |>
  filter(category == "Race") |>
  ggplot(aes(x = pct, y = source, fill = reorder(label, pct), alpha = source)) +
    geom_col(position = "stack") +
    scale_fill_hda(-1) +
    scale_alpha_discrete(range = c(0.6, 1)) +
    scale_x_continuous(labels = label_percent()) +
    guides(fill = guide_legend(reverse = TRUE),
           alpha = "none") +
    labs(title = "Client race and ethnicity compared to Charlottesville",
         subtitle = "Includes only DPL clients",
         fill = "Race") +
    theme_hda() +
    flip_gridlines() +
    theme(
      legend.position = "left",
      legend.justification = "left",
      legend.title = element_text(hjust = 0)
    )

ethnicity_plot <- race_join |>
  filter(category == "Ethnicity") |>
  ggplot(aes(x = pct, y = source, fill = reorder(label, pct), alpha = source)) +
    geom_col(position = "stack") +
```

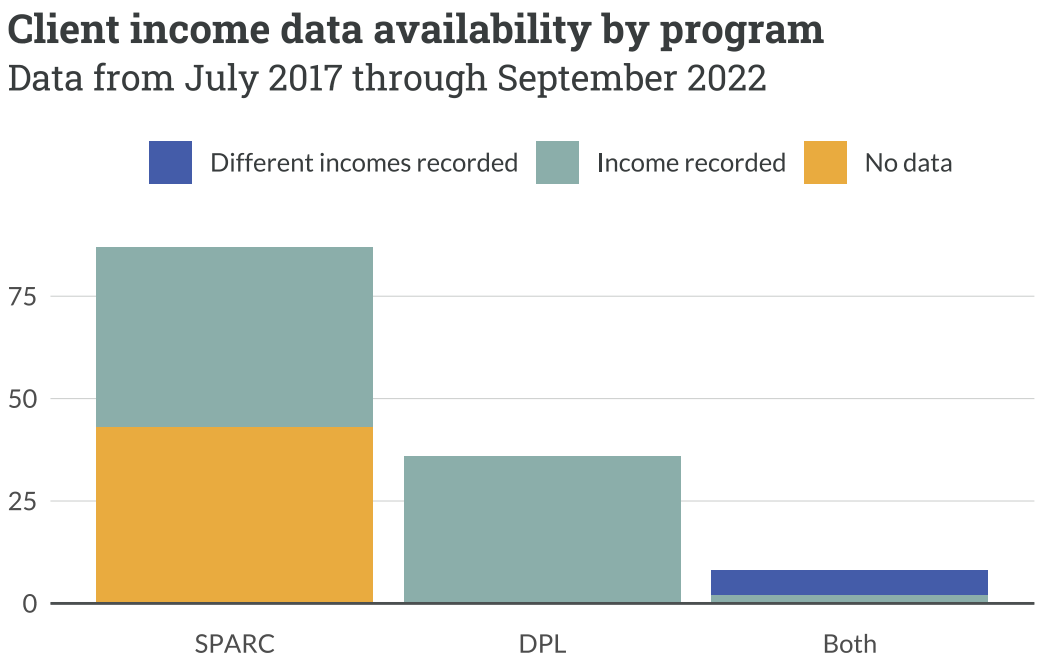
```
    scale_fill_hda(-1) +
    scale_alpha_discrete(range = c(0.6, 1)) +
    scale_x_continuous(labels = label_percent()) +
    guides(fill = guide_legend(reverse = TRUE),
           alpha = "none") +
    labs(fill = "Ethnicity",
         caption = "**Source:** U.S. Census Bureau, 2020 Decennial Census P.L. 94-171 Redi
    theme_hda() +
    flip_gridlines() +
    theme(
      legend.position = "left",
      legend.justification = "left",
      legend.title = element_text(hjust = 0)
    )

race_plot + ethnicity_plot +
  plot_layout(ncol = 1)
```



Source: U.S. Census Bureau, 2020 Decennial Census P.L. 94-171 Redistricting Data.

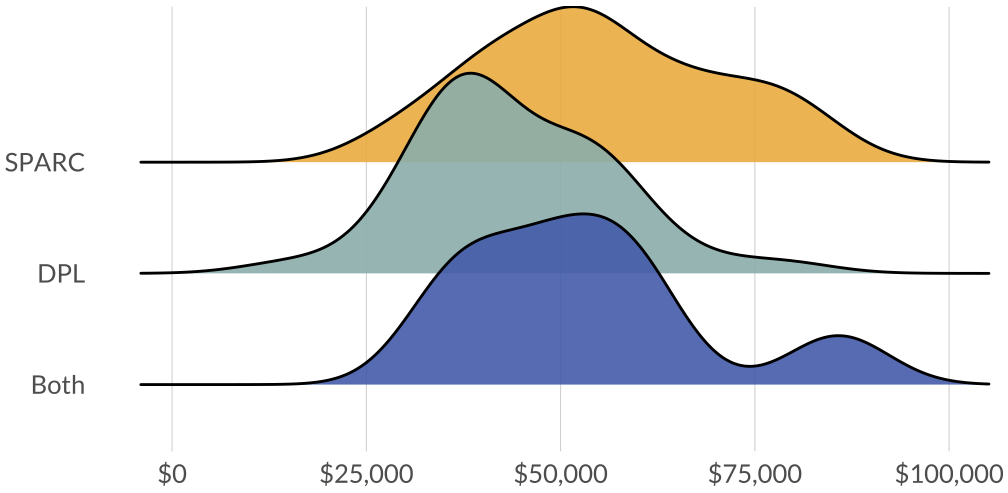
Household incomes are available for 88 of the 131 clients. Of the 43 clients with no income data, all are SPARC-only records. Six of the eight DPL clients who also used SPARC have two incomes recorded for each program—these values all differ, sometimes significantly.

```r
# Summarise clients by household income

clients_inc <- clients_all |>

  # Select only id_pha, program, and income columns

  select(1, 2, 9, 10, 11) |>

  # Combine DLP and SPARC incomes into one column

  mutate(income = case_when(
    !is.na(household_annual_income_dpl) & !is.na(household_annual_income_spc) ~ household_
    !is.na(household_annual_income_dpl) & is.na(household_annual_income_spc) ~ household_a
    is.na(household_annual_income_dpl) & !is.na(household_annual_income_spc) ~ household_a
    TRUE ~ NA_real_
  )) |>

  # Add column describing income data availability

  mutate(data = case_when(
    !is.na(household_annual_income_dpl) & !is.na(household_annual_income_spc) ~ "Different
    !is.na(household_annual_income_dpl) & is.na(household_annual_income_spc) ~ "Income rec
    is.na(household_annual_income_dpl) & !is.na(household_annual_income_spc) ~ "Income rec
    TRUE ~ "No data"
  ))

# Create plot showing income data availability

clients_inc |>
  group_by(program, data) |>
  summarise(n = n()) |>
  ggplot(aes(x = reorder(program, n, decreasing = TRUE), y = n, fill = data)) +
    geom_col(position = "stack") +
    scale_fill_hda() +
    labs(title = "Client income data availability by program",
         subtitle = "Data from July 2017 through September 2022") +
    theme_hda() +
    add_zero_line("y") +
    theme(
      legend.position = "top"
    )
```



Most of PHA's clients have household incomes between $25,000 and $60,000. However, the incomes of SPARC-only clients skew slightly higher, with some above $75,000.

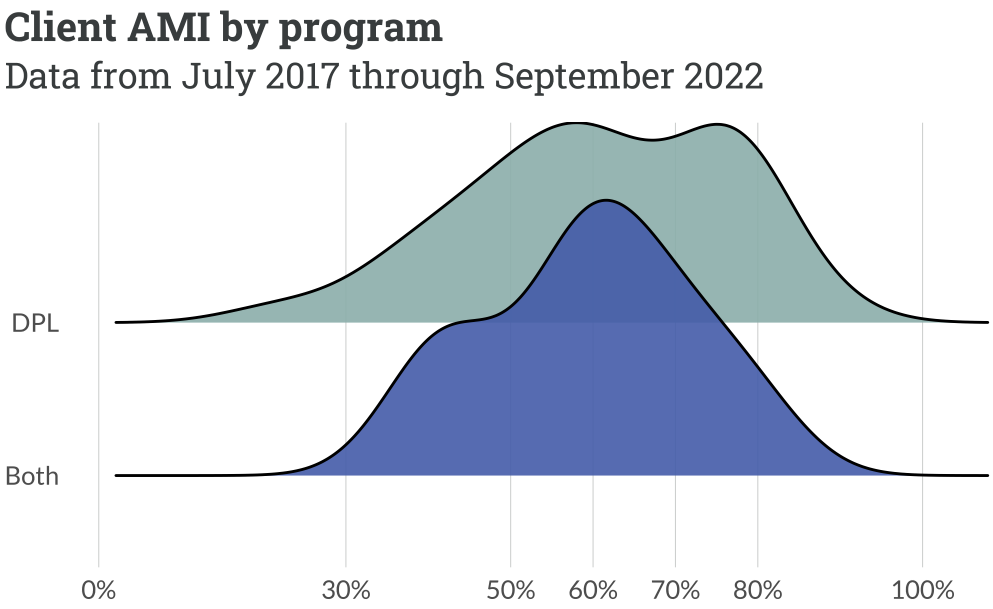
```
# Summarise income by program

ggplot(clients_inc, aes(x = income, y = program, fill = program)) +
  geom_density_ridges(alpha = 0.9) +
  scale_fill_hda() +
  scale_x_continuous(labels = label_dollar()) +
  labs(title = "Client household income by program",
       subtitle = "Data from July 2017 through September 2022",
       caption = "**Note:** Does not include 43 SPARC clients with no recorded income.") +
  theme_hda() +
  flip_gridlines()
```



Note: Does not include 43 SPARC clients with no recorded income.

Area median incomes (AMI) are calculated only for clients who used the DPL program. AMIs are most commonly between 50 and 80 percent, in line with program eligibility guidelines. On average, AMIs of the DPL clients who also used SPARC are slightly lower than those of clients who used DPL only.

```
# Summarise AMI by program

clients_inc |> filter(program != "SPARC") |>
ggplot(aes(x = client_ami, y = program, fill = program)) +
  geom_density_ridges(alpha = 0.9) +
  scale_fill_hda() +
  scale_x_continuous(labels = label_percent(), breaks = c(0, 0.3, 0.5, 0.6, 0.7, 0.8, 1))
  labs(title = "Client AMI by program",
       subtitle = "Data from July 2017 through September 2022",
       caption = "**Note:** Does not include 43 SPARC clients with no recorded income.") +
  theme_hda() +
  flip_gridlines()
```

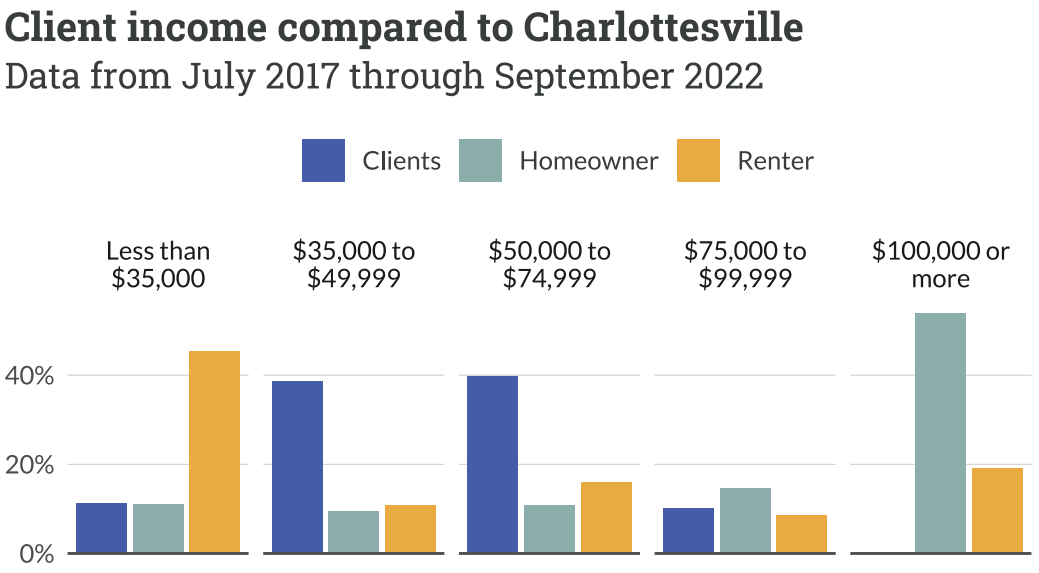


Note: Does not include 43 SPARC clients with no recorded income.

Compared to the distribution of household incomes in Charlottesville, clients are much more likely to earn more than most renters, while still making significantly less than most homeowners. Over 78 percent of clients earn between $35,000 and $75,000, versus just 27 percent of renters and 20 percent of homeowners.

```
# Assign client incomes to ACS categories

clients_inc_sum <- clients_inc |>
  mutate(income = case_when(
    income < 35000 ~ "Less than $35,000",
    income >= 35000 & income < 50000  ~ "$35,000 to $49,999",
    income >= 50000 & income < 75000  ~ "$50,000 to $74,999",
    income >= 75000 & income < 100000  ~ "$75,000 to $99,999",
    income >= 100000 ~ "$100,000 or more",
    TRUE ~ "No data"
  )) |>

  # Filter out clients with no income data (optional)

  filter(income != "No data") |>

  # Summarise clients by category
```

```
  count(income) |>

  # Get column names to match ACS data

  mutate(tenure = "Clients", .before = 1) |>
  rename(estimate = n)

# Join ACS income data with client income data

clients_cv_inc <- clients_inc_sum |>
  bind_rows(cv_income) |>

  # Add percentages

  group_by(tenure) |>
  mutate(pct = estimate/sum(estimate)) |>

  # Reorder income categories

  mutate(income = fct_relevel(
    income, "Less than $35,000", "$35,000 to $49,999", "$50,000 to $74,999",
    "$75,000 to $99,999", "$100,000 or more"))

# Create plot

ggplot(clients_cv_inc, aes(y = pct, x = tenure, fill = tenure)) +
  geom_col() +
  facet_wrap(~income, nrow = 1, labeller = label_wrap_gen(12)) +
  scale_y_continuous(labels = label_percent()) +
  scale_fill_hda() +
  labs(title = "Client income compared to Charlottesville",
       subtitle = "Data from July 2017 through September 2022",
       caption = "**Source:** U.S. Census Bureau, American Community Survey, 2017-2021 5-y
  theme_hda() +
  add_zero_line("y") +
  theme(axis.text.x = element_blank(),
        legend.position = "top")
```

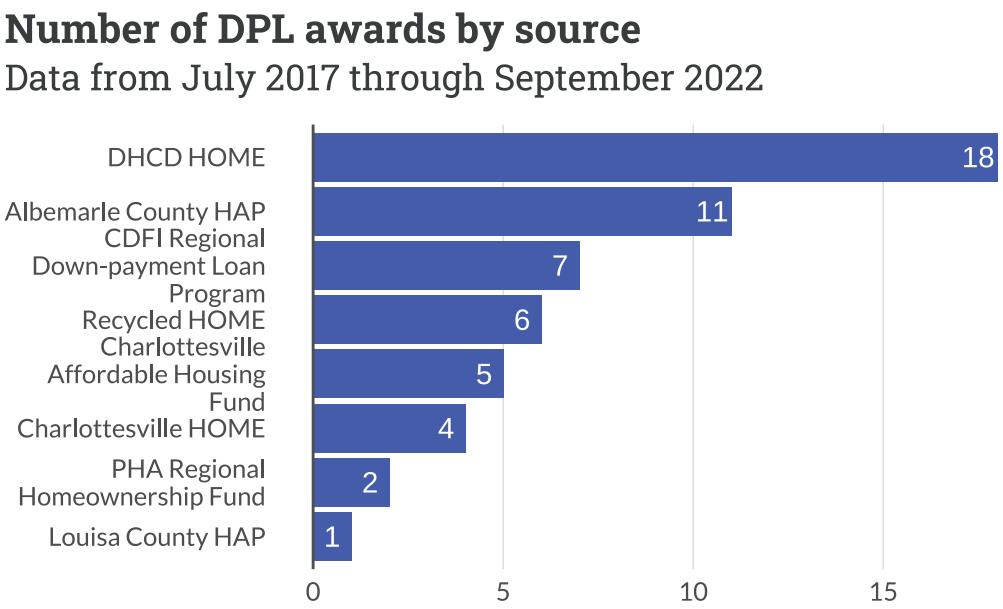


Assistance levels

PHA's DPL program uses funds from a number of different sources. Clients were most commonly supported by HOME funds from DHCD (18) and from Albemarle County's Homebuyer Assistance Program (11). Overall, PHA has used eight separate sources to fund its DPL program.

```
dpl_sources <- clients_all |>
  filter(program != "SPARC") |>
  select(1, 2, 36:43) |>
  pivot_longer(
    cols = c(3:10),
    names_to = "source",
    values_to = "x"
  ) |>
  group_by(source) |>
  summarise(count = sum(x)) |>
  mutate(source = case_when(
    source == "dhcd" ~ "DHCD HOME",
    source == "achap" ~ "Albemarle County HAP",
    source == "cdfi" ~ "CDFI Regional Down-payment Loan Program",
```

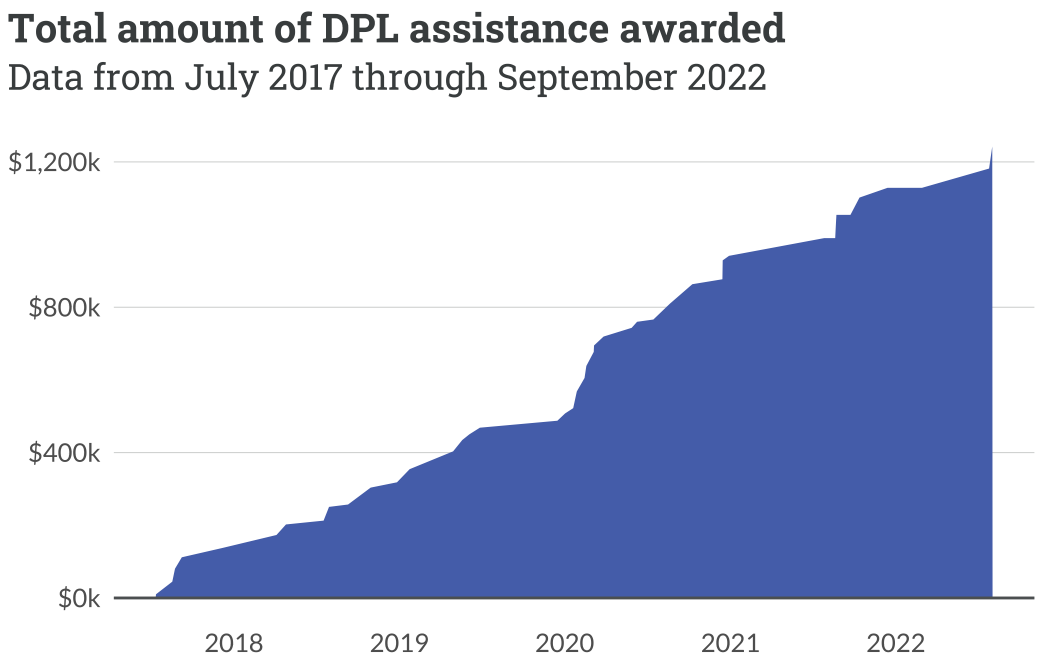
```
    source == "recycled_home" ~ "Recycled HOME",
    source == "cahf" ~ "Charlottesville Affordable Housing Fund",
    source == "city" ~ "Charlottesville HOME",
    source == "pha_regional" ~ "PHA Regional Homeownership Fund",
    source == "lchap" ~ "Louisa County HAP",
    TRUE ~ str_to_upper(source)
  )) |>
  mutate(source = str_wrap(source, 20))

ggplot(dpl_sources, aes(x = count, y = reorder(source, count), label = count)) +
  geom_col(fill = "#445ca9") +
  geom_text(color = "#FFFFFF", nudge_x = -0.5) +
  theme_hda() +
  flip_gridlines() +
  add_zero_line("x") +
  labs(
    title = "Number of DPL awards by source",
    subtitle = "Data from July 2017 through September 2022",
    caption = "**Notes:** 'HAP' = Homebuyer Assistance Program."
  )
```



PHA awarded a total of $1,242,190 in DPL assistance from July 2017 to September 2022.

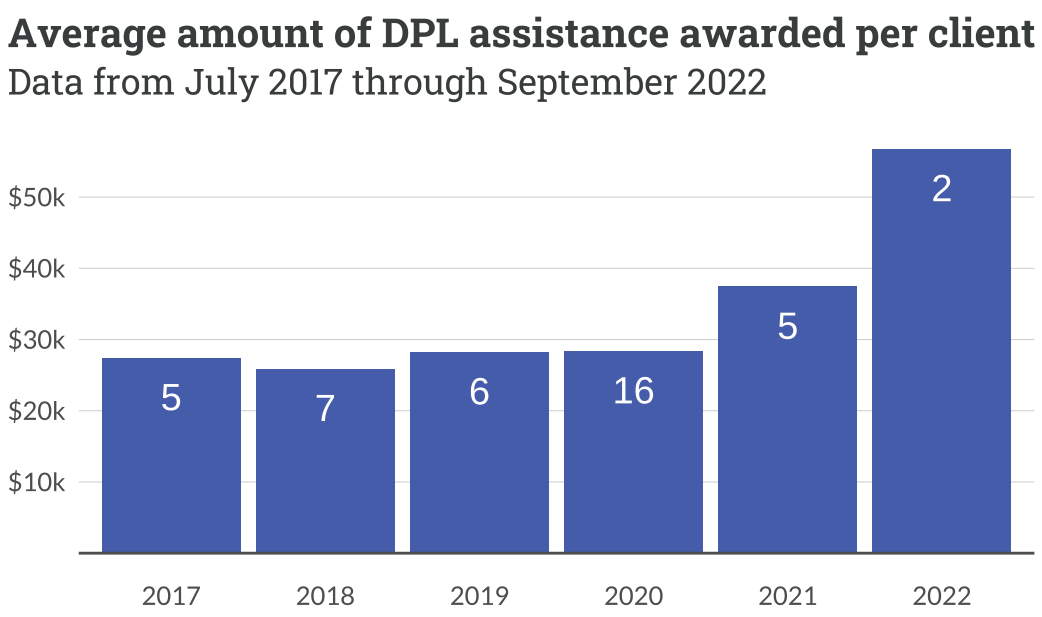
This amounted to roughly $28,230 provided per client.

```
dpl_amount <- clients_all |>
  drop_na("close_date_dpl") |>
  arrange(close_date_dpl) |>
  mutate(cum_sum = cumsum(pha_loans_amount))

ggplot(dpl_amount, aes(x = close_date_dpl, y = cum_sum)) +
  geom_area(fill = "#445ca9") +
  scale_y_continuous(labels = label_dollar(scale = 0.001, suffix = "k")) +
  add_zero_line("y") +
  theme_hda() +
  labs(
    title = "Total amount of DPL assistance awarded",
    subtitle = "Data from July 2017 through September 2022"
  )
```



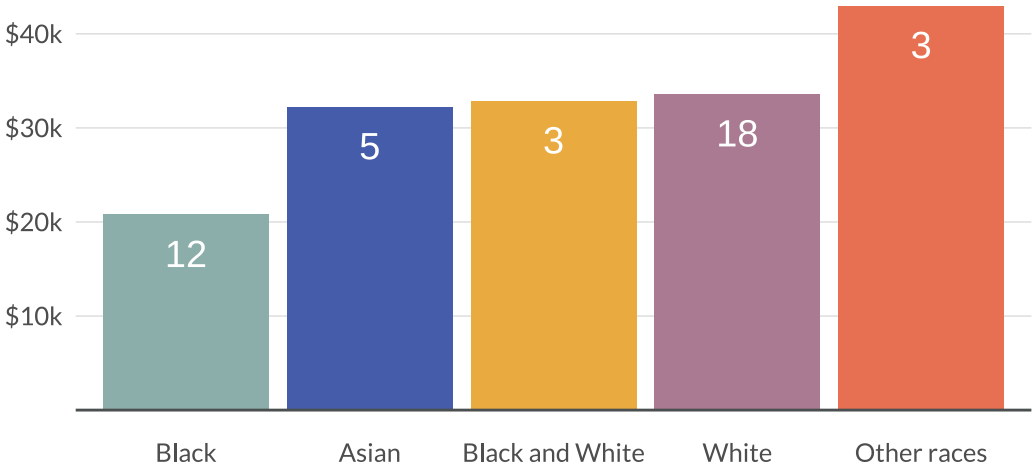
The average amount each client received stayed around $28,000 from 2017 through 2020. In 2021, that average increased to $37,435. In 2022, the two clients that received DPL each received significant DPL assistance well above prior year averages.

```r
dpl_annual <- dpl_amount |>
  mutate(year = format(close_date_dpl, format = "%Y")) |>
  filter(pha_loans_amount != 0) |>
  group_by(year) |>
  summarise(avg = mean(pha_loans_amount),
            clients = n())

ggplot(dpl_annual, aes(x = year, y = avg, label = clients)) +
  geom_col(fill = "#445ca9") +
  geom_text(vjust = 2,
            color = "white",
            size = 5) +
  scale_y_continuous(labels = label_dollar(scale = 0.001, suffix = "k"),
                     breaks = c(10000, 20000, 30000, 40000, 50000)) +
  add_zero_line("y") +
  theme_hda() +
  labs(
    title = "Average amount of DPL assistance awarded per client",
    subtitle = "Data from July 2017 through September 2022",
    caption = "**Note:** Bars show total number of clients for that group."
  )
```



Black clients were the only race with an average DPL amount ($20,761) below the overall average. Asian, Black and White, and White-alone clients all had averages between $32,000 and $34,000. Three clients of another race tallied a notably higher average at $42,973.

```
dpl_race <- dpl_amount |>
  filter(pha_loans_amount != 0) |>
  group_by(race) |>
  summarise(avg = mean(pha_loans_amount),
            clients = n())

ggplot(dpl_race, aes(x = reorder(race, avg), y = avg, fill = race, label = clients)) +
  geom_col() +
  geom_text(vjust = 2,
            color = "white",
            size = 5) +
  scale_fill_hda() +
  scale_y_continuous(labels = label_dollar(scale = 0.001, suffix = "k"),
                     breaks = c(10000, 20000, 30000, 40000, 50000)) +
  add_zero_line("y") +
  theme_hda() +
  labs(
    title = "Average amount of DPL assistance awarded by race",
    subtitle = "Data from July 2017 through September 2022",
    caption = "**Note:** Bars show total number of clients for that group."
  )
```

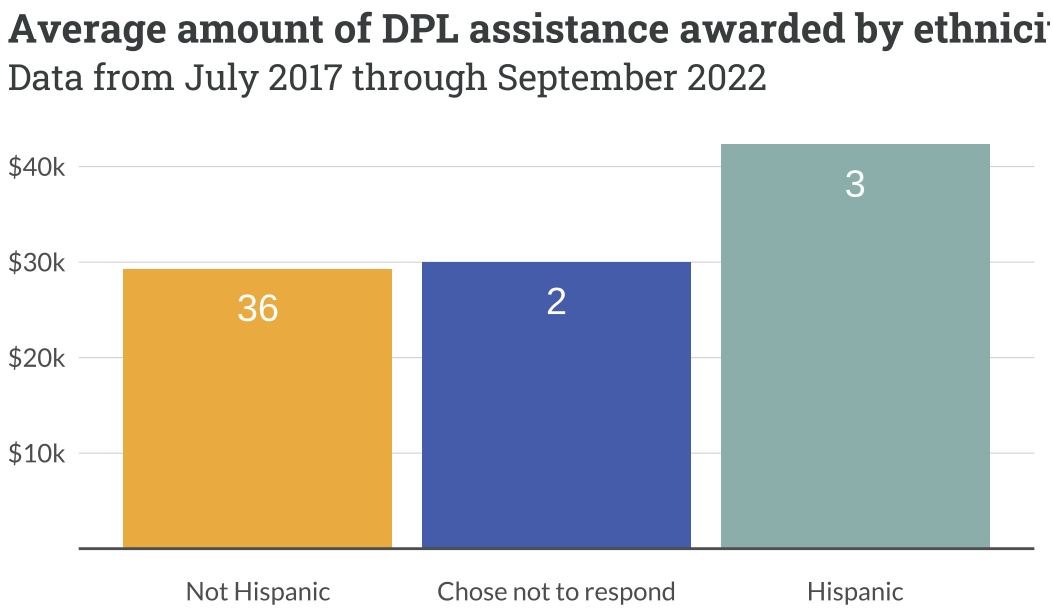


Note: Bars show total number of clients for that group.

Only five total clients were Hispanic or chose not to respond when asked their ethnicity. As a result, the average DPL amount for non-Hispanic clients ($29,310) is very close to the overall client average. Among the three clients who were Hispanic, their average DPL amounted to a much larger $42,316.

```
dpl_ethnicity <- dpl_amount |>
  filter(pha_loans_amount != 0) |>
  group_by(ethnicity) |>
  summarise(avg = mean(pha_loans_amount),
            clients = n())

ggplot(dpl_ethnicity, aes(x = reorder(ethnicity, avg), y = avg, fill = ethnicity, label =
  geom_col() +
  geom_text(vjust = 2,
            color = "white",
            size = 5) +
  scale_fill_hda() +
  scale_y_continuous(labels = label_dollar(scale = 0.001, suffix = "k"),
                     breaks = c(10000, 20000, 30000, 40000, 50000)) +
  add_zero_line("y") +
  theme_hda() +
  labs(
```

```
  title = "Average amount of DPL assistance awarded by ethnicity",
  subtitle = "Data from July 2017 through September 2022",
  caption = "**Note:** Bars show total number of clients for that group."
)
```



Spatial patterns

> **Note**
>
> Client and property location data is only available for clients who used the DPL program.

```
# Get list of all localities in Virginia

va_localities <- list_counties("VA")

# Get all census tracts for Virginia

va_tracts <- tracts(state = "VA") |>
  left_join(va_localities, by = c("COUNTYFP" = "county_code")) |>
```

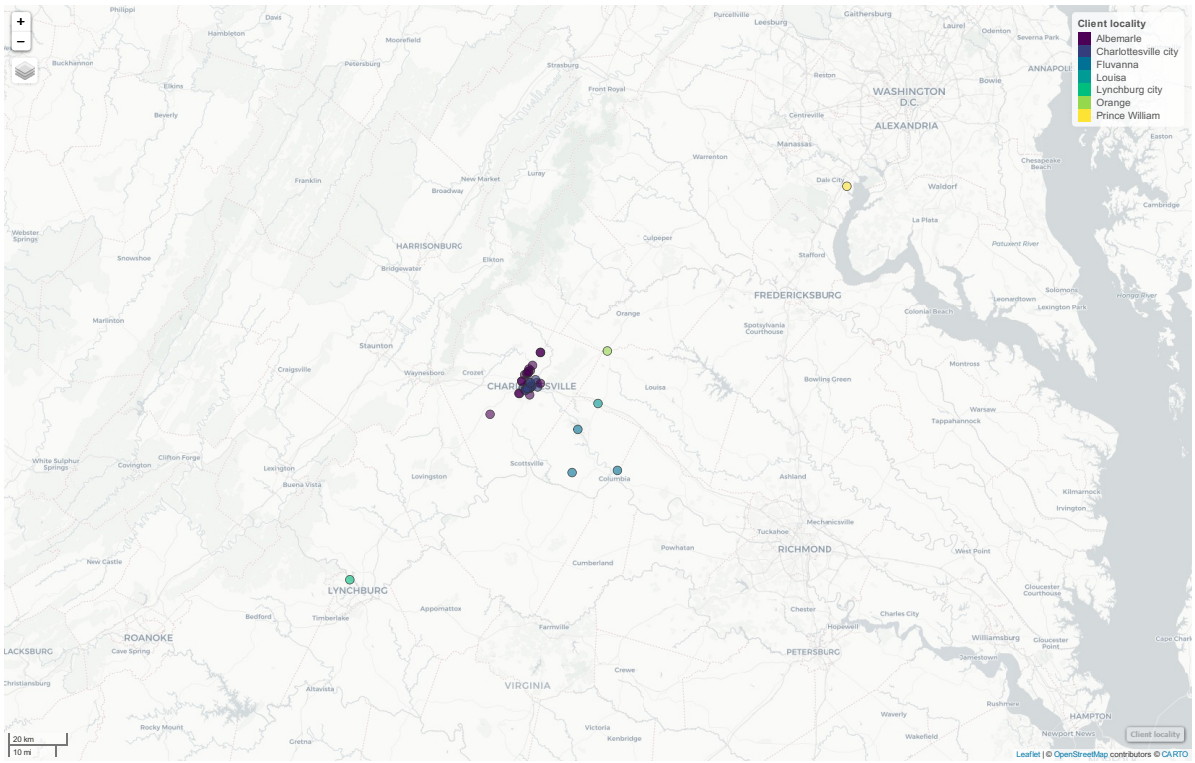
```
  st_transform(4502)

# Geocode client addresses

clients_geocode <- clients_all |>
  geocode(street = client_street_address, state = client_state,
          city = client_city, postalcode = client_zip,
          method = "geocodio",
          lat = lat,
          long = long) |>

  # Drop SPARC entries with no address data

  drop_na(lat) |>

  # Specify WGS 1984 coordinate system for lat/long data

  st_as_sf(coords = c("long", "lat"),
           remove = FALSE,
           crs = 4326) |>

  # Project into Virginia State Plane South

  st_transform(4502)

# Spatial join client data with tracts and localities

clients_sf <- st_join(clients_geocode, va_tracts) |>
  rename(Locality = county)

# Geocode property addresses

property_geocode <- clients_all |>
  geocode(street = property_street_address, state = property_state,
          city = property_city, postalcode = property_zip,
          method = "geocodio",
          lat = lat,
          long = long) |>

  # Drop SPARC entries with no address data
```

```
  drop_na(lat) |>

  # Specify WGS 1984 coordinate system for lat/long data

  st_as_sf(coords = c("long", "lat"),
           remove = FALSE,
           crs = 4326) |>

  # Project into Virginia State Plane South

  st_transform(4502)

# Spatial join client data with tracts and localities

property_sf <- st_join(property_geocode, va_tracts) |>
  rename(Locality = county)

# Save data

write_rds(clients_sf, "data/clients_sf.rds")
write_rds(property_sf, "data/property_sf.rds")
```

Client origins

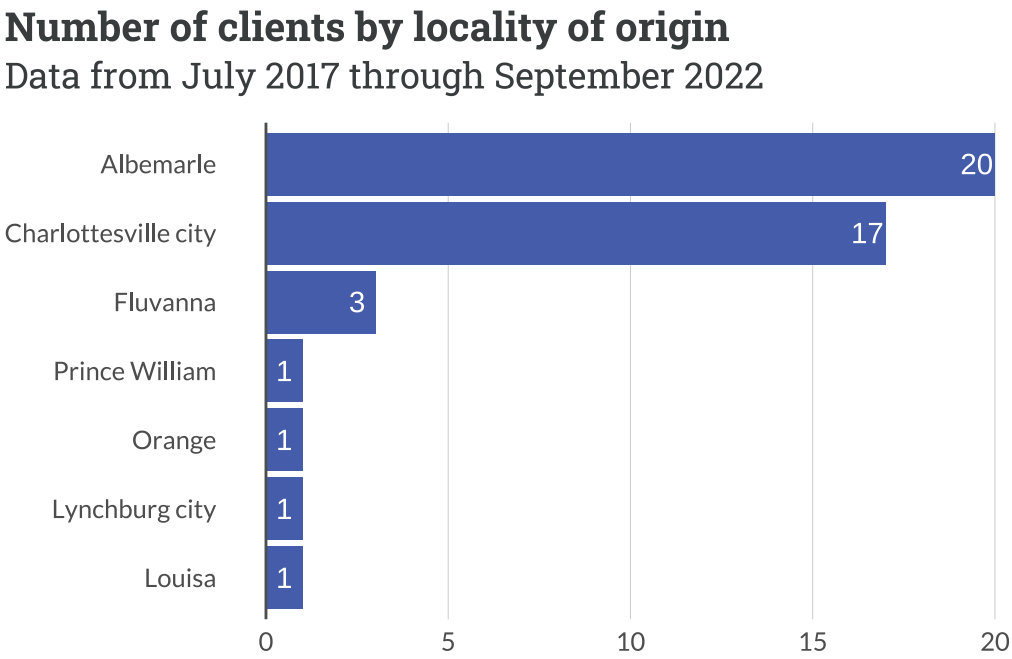
The map below shows the original addresses of each client, i.e. where they lived when they applied for DPL assistance.

```
# Make map of clients

clients_sf <- read_rds("data/clients_sf.rds")

mapview(
  clients_sf,
  zcol = "Locality",
  layer.name = "Client locality",
  label = FALSE,
  popup = FALSE
)
```



Most clients lived in either Albemarle (20) or Charlottesville (17) when they applied to the DPL program. Three clients also came from Fluvanna, while all other origin localities has one client each.

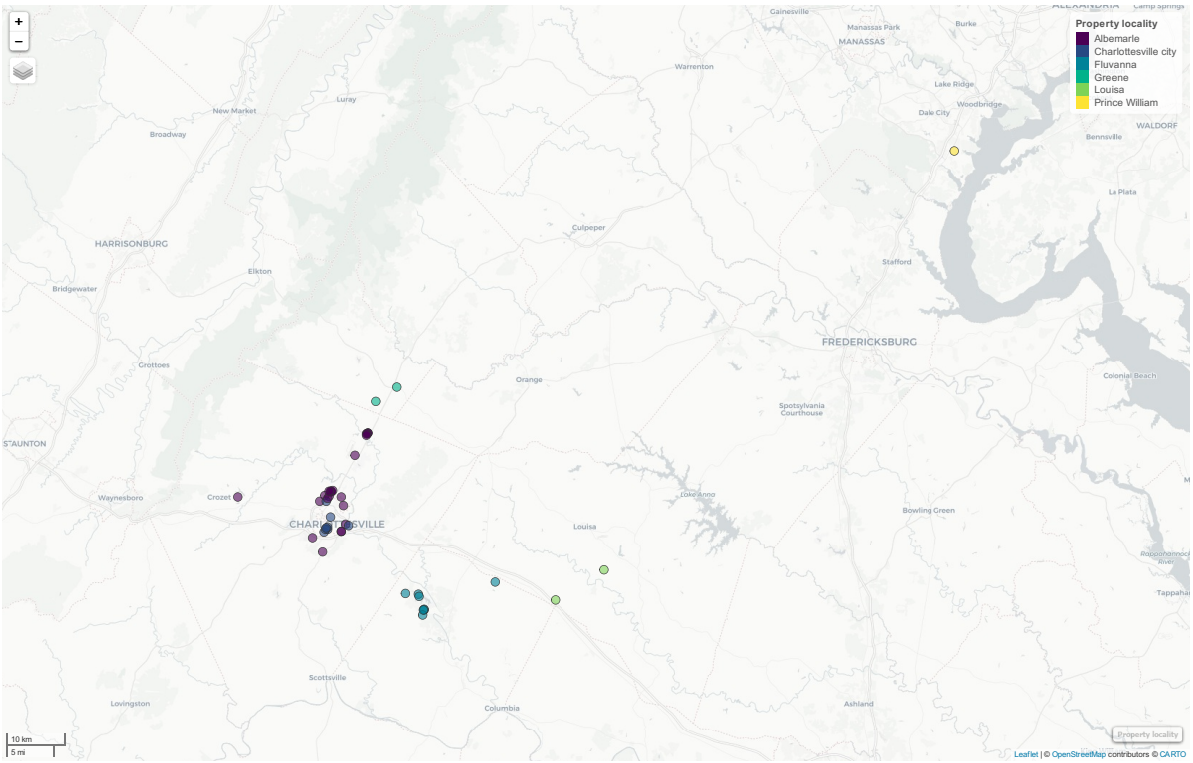
```
clients_locality <- clients_sf |>
  count(Locality)

ggplot(clients_locality, aes(x = n, y = reorder(Locality, n), label = n)) +
  geom_col(fill = "#445ca9") +
  geom_text(color = "#FFFFFF", nudge_x = -0.5) +
  theme_hda() +
  flip_gridlines() +
  add_zero_line("x") +
  labs(
    title = "Number of clients by locality of origin",
    subtitle = "Data from July 2017 through September 2022"
  )
```



Client destinations

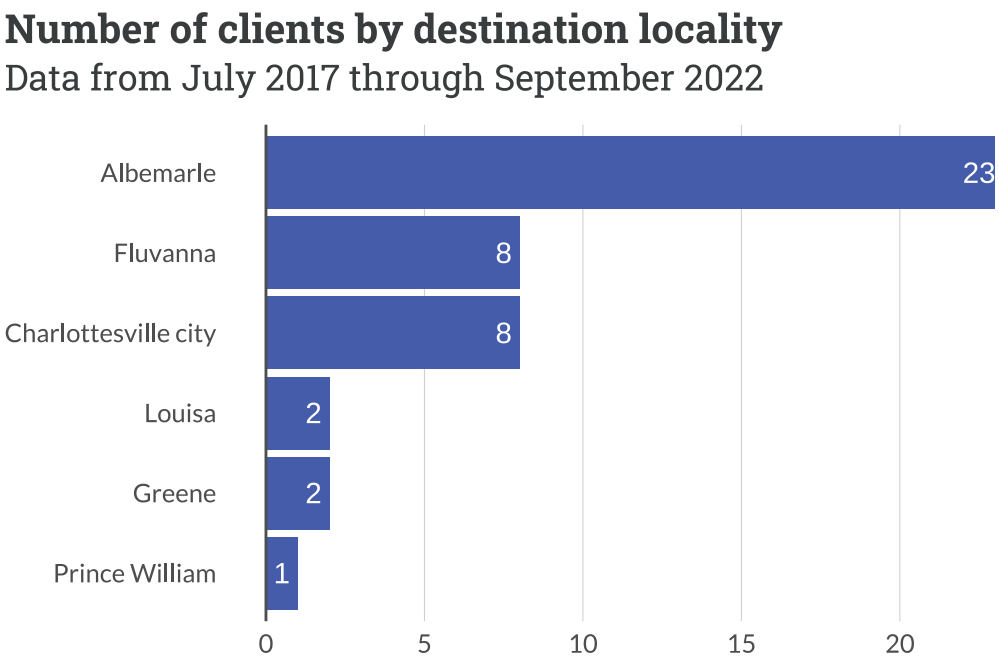
The map below shows the addresses of homes purchased by clients, i.e. where they moved after using the DPL program.

```
# Make map of properties

property_sf <- read_rds("data/property_sf.rds")

mapview(
  property_sf,
  zcol = "Locality",
  layer.name = "Property locality",
  label = FALSE,
  popup = FALSE
)
```



The majority of homes purchased by clients were in Albemarle (22), followed by Charlottesville (9) and Fluvanna (8). Two or fewer clients purchased homes in each of the other localities.

```
property_locality <- property_sf |>
  count(Locality)

ggplot(property_locality, aes(x = n, y = reorder(Locality, n), label = n)) +
  geom_col(fill = "#445ca9") +
  geom_text(color = "#FFFFFF", nudge_x = -0.5) +
  theme_hda() +
  flip_gridlines() +
  add_zero_line("x") +
  labs(
    title = "Number of clients by destination locality",
    subtitle = "Data from July 2017 through September 2022"
  )
```

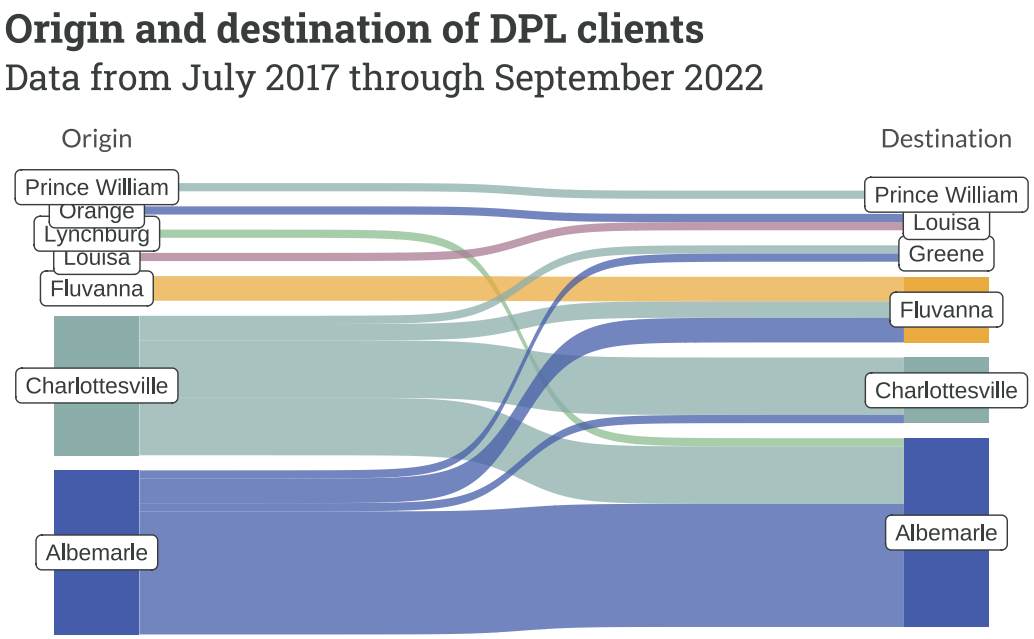


Client moves

Most of PHA's DPL clients moved from, moved to, or stayed in Albemarle County or the City of Charlottesville. A similar number of clients were originally from Albemarle (20) and Charlottesville (17), with only seven from elsewhere. Albemarle was the most common destination (22), followed by Charlottesville (9), and Fluvanna (8).

```
library(ggsankey)

client_moves <- st_drop_geometry(clients_sf) |>
  left_join(st_drop_geometry(property_sf), "id_pha") |>
  select("Origin" = 'Locality.x', "Destination" = 'Locality.y') |>
  mutate(across(1:2, ~ str_remove_all(.x, " city")))

client_sankey <- client_moves |>
  make_long(Origin, Destination)

ggplot(client_sankey, aes(x = x, next_x = next_x,
                          node = node, next_node = next_node,
                          fill = node, label = node)) +
  geom_sankey(flow_alpha = 0.75, smooth = 15) +
```

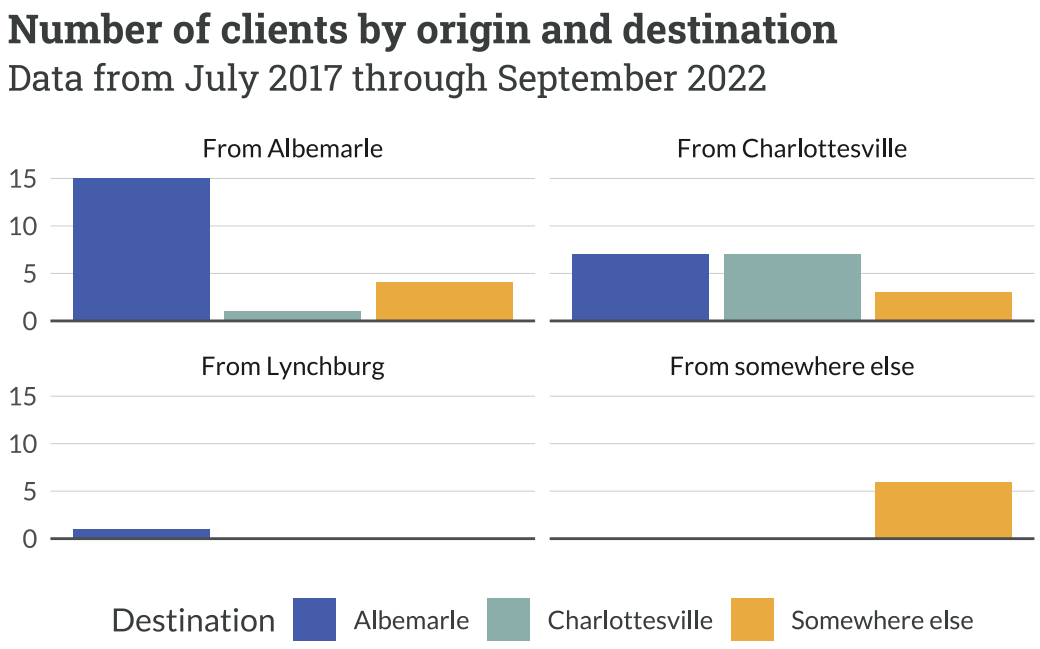
```
  geom_sankey_label(fill = "white", colour = "#383c3d", size = 3) +
  scale_fill_hda(repeat_pal = TRUE) +
  scale_x_discrete(expand = c(0.05, 0.05), position = "top") +
  theme_hda() +
  theme(axis.text.y = element_blank(),
        panel.grid.major.y = element_blank()) +
  labs(
    title = "Origin and destination of DPL clients",
    subtitle = "Data from July 2017 through September 2022"
  )
```



Among all clients from Albemarle, most stayed in the county, or to another county. Only one moved into Charlottesville. Just seven of the 17 clients from Charlottesville stayed in the city; the same number moved into Albemarle and the remainder to other counties.

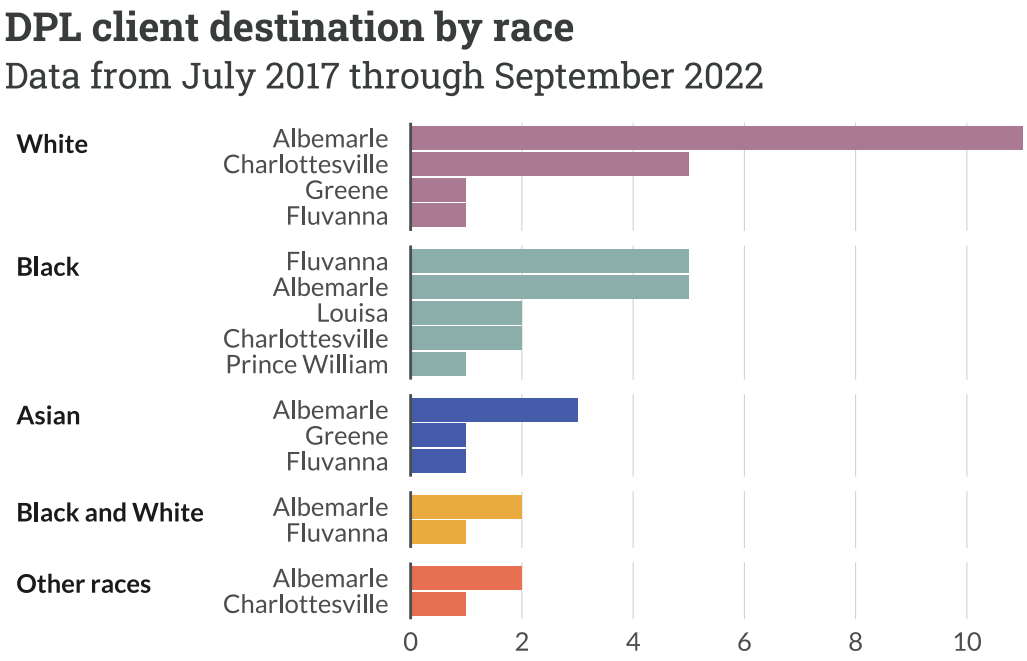
```
client_moves_sum <- client_moves |>
  mutate(move = case_when(
    Origin == Destination ~ "Stayed",
    TRUE ~ "Moved"
  )) |>
  mutate(origin_sum = case_when(
```

```
    Origin %in% c("Fluvanna", "Louisa", "Lynchburg city", "Orange", "Prince William") ~ "F
    TRUE ~ str_c("From ", Origin)
  )) |>
  mutate(destination_sum = case_when(
    Destination %in% c("Fluvanna", "Louisa", "Greene", "Prince William") ~ "Somewhere else
    TRUE ~ Destination
  ))

ggplot(client_moves_sum, aes(x = destination_sum, fill = destination_sum)) +
  facet_wrap(~origin_sum) +
  geom_bar() +
  scale_fill_hda() +
  theme_hda() +
  add_zero_line("y") +
  theme(legend.position = "bottom",
        legend.title = element_text(),
        axis.text.x = element_blank()) +
  labs(
    title = "Number of clients by origin and destination",
    subtitle = "Data from July 2017 through September 2022",
    fill = "Destination"
  )
```



Most white clients purchased homes in Albemarle (10), followed by Charlottesville (5). Among the 15 Black clients, 5 bought in Albemarle, 4 in Fluvanna, 2 each in Louisa and Charlottesville, and 1 each in Suffolk and Prince William.

```
library(tidytext)

client_moves_race <- st_drop_geometry(clients_sf) |>
  left_join(st_drop_geometry(property_sf), "id_pha") |>
  select("race" = 'race.x', "Origin" = 'Locality.x', "Destination" = 'Locality.y') |>
  mutate(across(2:3, ~ str_remove_all(.x, " city"))) |>
  group_by(race, Destination) |>
  summarise(n = n()) |>
  mutate(race = fct_relevel(race, "White", "Black", "Asian"),
         Destination = reorder_within(Destination, n, race))

ggplot(client_moves_race, aes(x = n, y = Destination, fill = race)) +
  facet_grid(rows = vars(fct_relevel(race, "White", "Black", "Asian")), scales = "free_y",
  geom_col() +
  scale_x_continuous(
    breaks = seq(0, 10, 2),
    labels = label_number(accuracy = 1),
    expand = c(0.01, 0.05)
    ) +
  scale_y_reordered() +
  scale_fill_hda() +
  add_zero_line("x") +
  theme_hda(flip_gridlines = TRUE) +
  theme(
    strip.text.y.left = element_text(angle = 0, face = "bold", vjust = 1, hjust = 0),
    strip.placement = "outside"
  ) +
  labs(
    title = "DPL client destination by race",
    subtitle = "Data from July 2017 through September 2022"
  )
```



Housing outcomes

The median sales price for all clients was $224,500, but those prices vary significantly by program.

```
# Summarise home sales price by program

clients_inc_price <- clients_all |>

  # Select only id_pha, program, income, home sales price, and race columns

  select(1, 2, 9, 10, 20, 21, 53) |>

  # Combine DLP and SPARC incomes into one column

  mutate(income = case_when(
    !is.na(household_annual_income_dpl) & !is.na(household_annual_income_spc) ~ household_
    !is.na(household_annual_income_dpl) & is.na(household_annual_income_spc) ~ household_a
    is.na(household_annual_income_dpl) & !is.na(household_annual_income_spc) ~ household_a
    TRUE ~ NA_real_
  )) |>
```

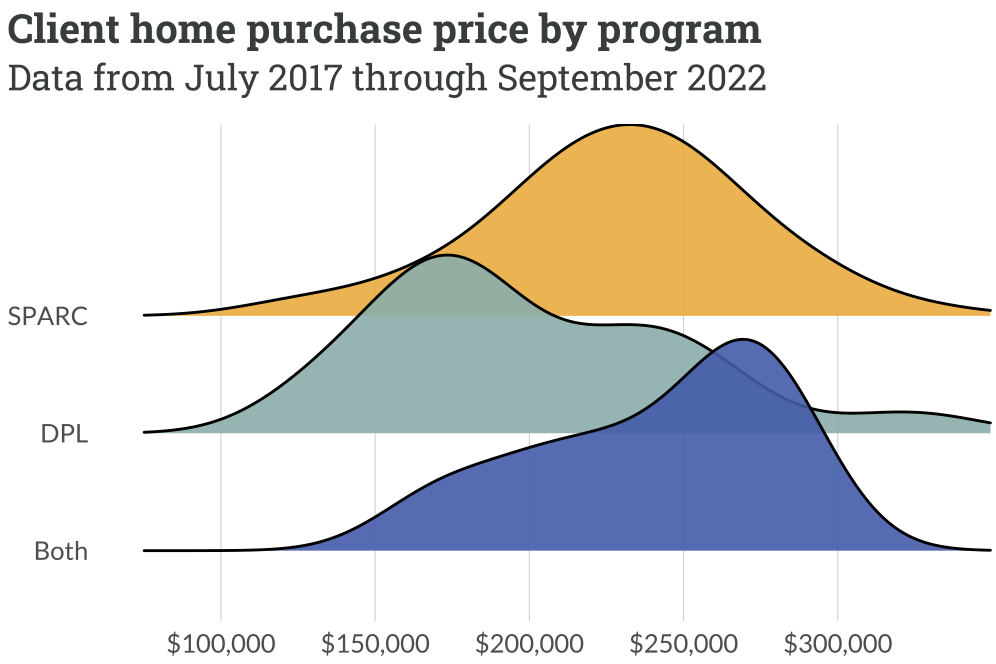
Program	Clients	Median sales price	Mean sales price
Both	8	$254,050	$241,363
SPARC	86	$228,800	$226,923
DPL	36	$184,753	$200,497

```
  # Combine DLP and SPARC sales prices into one column

  mutate(price = case_when(
    !is.na(sale_price_dpl) ~ sale_price_dpl,
    TRUE ~ sale_price_spc
  ))

# Generate table

clients_inc_price |>
  drop_na(price) |>
  group_by(program) |>
  summarise(n = n(),
            median = median(price),
            mean = mean(price)) |>
  mutate(across(3:4, ~ formattable::currency(.x, digits = 0))) |>
  arrange(desc(median)) |>
  kable(col.names = c("Program", "Clients", "Median sales price", "Mean sales price")) |>
  kableExtra::kable_styling(
    bootstrap_options = c("striped", "hover", "condensed", "responsive")
  )
```

Home prices were lowest for DPL-only clients, with most between $150,000 and $200,000. SPARC-only clients purchased homes generally between $200,000 and $250,000. Clients who used both programs were able to purchase homes at higher prices, on average, than all other clients.

```
ggplot(clients_inc_price, aes(x = price, y = program, fill = program)) +
  geom_density_ridges(alpha = 0.9) +
  scale_fill_hda() +
  scale_x_continuous(labels = label_dollar(),
                     limits = c(75000, 350000),
                     breaks = c(100000, 150000, 200000, 250000, 300000)) +
  labs(title = "Client home purchase price by program",
       subtitle = "Data from July 2017 through September 2022") +
```

```
  theme_hda() +
  flip_gridlines()
```

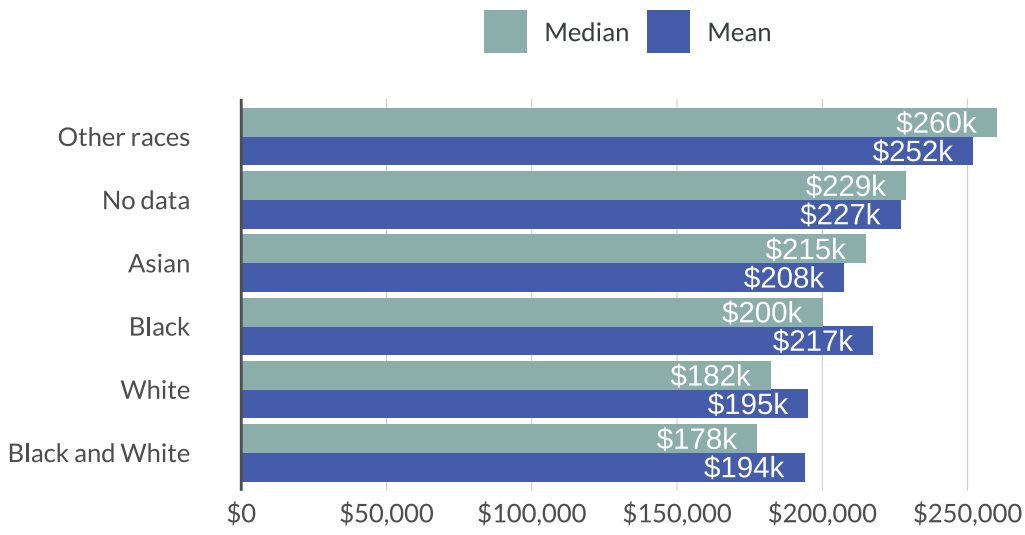


Average home prices also vary by race. Clients identifying as another race have the highest average, surpassing $250,000, although this includes only three buyers. Clients whose records do not include their race also have high average prices around $227,000. These are nearly all SPARC-only clients.

Asian and Black clients have average home prices slightly below the average for all clients, followed by clients who are White or who are White and Black. Those clients have average home prices well below $200,000.

```
clients_price_race <- clients_inc_price |>
  drop_na(price) |>
  group_by(race) |>
  summarise(n = n(),
            Mean = mean(price),
            Median = median(price)) |>
  mutate(race = replace_na(race, "No data")) |>
  pivot_longer(3:4, names_to = "stat", values_to = "value")
```

```
ggplot(clients_price_race, aes(x = value, y = reorder(race, value),
                               fill = stat,
                               label = label_dollar(accuracy = 1, scale = 0.001, suffix =
  geom_col(position = "dodge") +
  geom_text(color = "white", hjust = 1.25, position = position_dodge(0.9)) +
  scale_fill_hda() +
  scale_x_continuous(labels = label_dollar(),
                     breaks = c(0, 50000, 100000, 150000, 200000, 250000)) +
  labs(title = "Average client home purchase price by race",
       subtitle = "Data from July 2017 through September 2022") +
  theme_hda() +
  flip_gridlines() +
  add_zero_line("x") +
  theme(legend.position = "top") +
  guides(fill = guide_legend(reverse = TRUE))
```




```
# Client home attributes and price compared to neighborhood
# Client loan products compared to region (and neighborhood, if possible)
```

Home equity

This section explores methods for estimating the amount of home equity that clients have earned since the purchase of their home.

Home equity is defined as:

$$E = V - B$$

- E = Home equity
- V = Current market value of home
- B = Remaining loan balance

The data provided by PHA allows us to accurately calculate a client's remaining loan balance. However, an accurate figure for a home's current value would require a very recent arms-length sale or appraisal. Since these are not available for all homes in the dataset, we will estimate the current value with alternative data sources.

Two different methods for projecting equity will be used: the first uses annual property assessment values, while the second uses property sales records also collected by the local assessor.

Estimating equity via assessments

The steps below show the process for estimating home equity for a sample of clients in the City of Charlottesville who purchased their home in 2017, when DPL data is first available.

Step 1: Select clients

Select the earliest recorded DPL clients who purchased a home in the City of Charlottesville in 2017. This gives us the longest ownership timeframe for accruing home equity.

```
prop_2017 <- property_sf |>

  # Select clients with close dates in 2017

  filter(as_date(close_date_dpl) < as_date("2018-01-01")) |>

  # Homes purchased in Charlottesville only

  filter(Locality == "Charlottesville city") |>
```

```
  # Keep only necessary columns

  select(id_pha, close_date_dpl, property_street_address, sale_price_dpl,
         appraised_value, mortgage_amount_dpl, interest_rate_dpl, GEOID)
```

Step 2: Assign neighborhoods

Determine which neighborhoods the homes are in. The averages for these neighborhoods will be used as benchmarks. Neighborhood boundaries are the Planning Neighborhood Areas from the City of Charlottesville.

```
# Load in Charlottesville residential parcels

cv_parcels <- read_rds("data/cv_parcels.rds")

# Load in Charlottesville neighborhood boundaries

cv_nhoods <- st_read("data/shp/Planning_Neighborhood_Area.shp", quiet = TRUE) |>
    st_transform(4502)

# Spatial join with neighborhoods and parcel records

prop_2017 <- prop_2017 |>
  st_join(cv_nhoods) |>
  st_join(cv_parcels)
```

Step 3: Find change in neighborhood assessments

Calculate the change in median assessed value from 2017 to 2022 for each neighborhood. Only single-family residential parcels are included.

```
# Spatial join all parcels to neighborhoods

cv_parcels_nhood <- cv_parcels |>

  # Convert parcels to centroid points

  st_centroid() |>

  # Spatial join

  st_join(cv_nhoods) |>
```

```
  # Join annual assessment data by parcel
  left_join(cv_assess, by = "ParcelNumber")

# Calculate median values by year
cv_value_nhood <- cv_parcels_nhood |>
  # Drop geometry
  st_drop_geometry() |>
  # Group by neighborhood and year
  group_by(NAME, TaxYear) |>
  # Calculate groupwise median
  summarise(assessment = median(TotalValue)) |>
  # Filter to neighborhoods where homes are
  filter(NAME %in% c("The Meadows", "Fifeville")) |>
  # Add field to mark values as neighborhood average
  mutate(value = "Neighborhood average")
```

Step 4: Compare change in client and neighborhood assessments

Calculate the percent change in assessed value for client homes and their respective neighborhoods.

```
# Combine percent change in assessments for homes and neighborhoods
prop_assess <- prop_2017 |>
  # Drop geometry
  st_drop_geometry() |>
```

```
# Join annual assessment data by parcel

left_join(cv_assess, by = "ParcelNumber") |>

# Keep only necessary columns

select(NAME, TaxYear, assessment = TotalValue) |>

# Add field to mark values as client home

mutate(value = "Client home") |>

# Add neighborhood values

bind_rows(cv_value_nhood) |>

# Group by value designation and neighborhood

group_by(value, NAME) |>

# Arrange ascending by year

arrange(TaxYear) |>

# Calculate cumulative percent change

mutate(chg = assessment - first(assessment),
       pct_chg = chg / first(assessment))
```

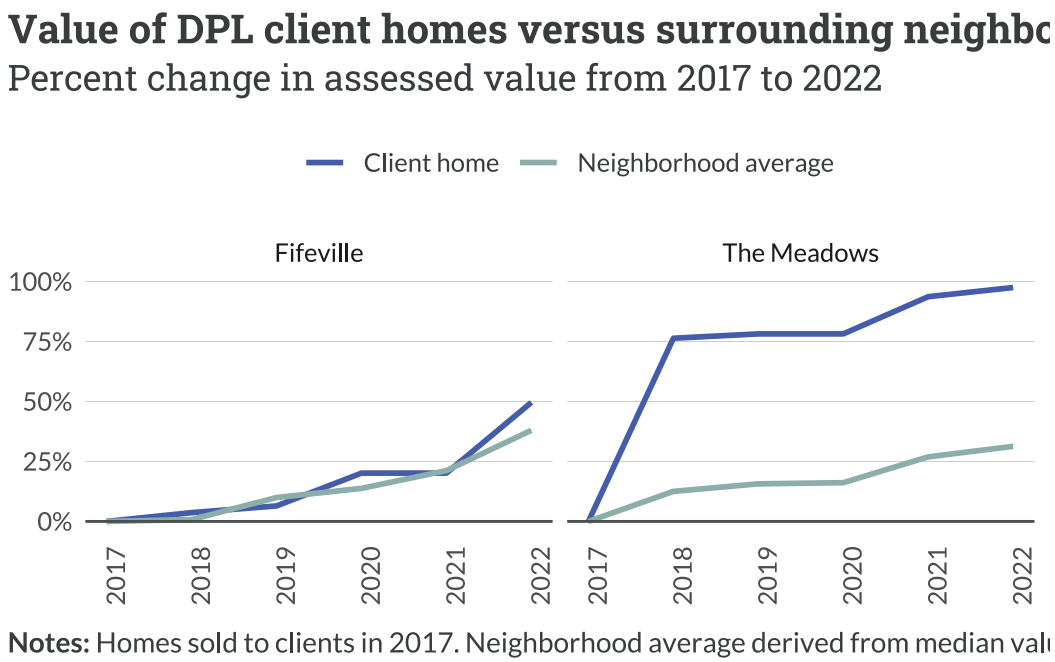
Following the methods above leaves us with two homes within the City of Charlottesville that DPL clients purchased in 2017. These homes are located on the following blocks and neighborhoods.

- 2300 block of North Berkshire Road (Fifeville)
- 800 block of Orangedale Avenue (The Meadows)

Exact addresses are omitted from this narrative for privacy.

The chart below demonstrates how we can compare the change in assessed value for homes purchased by clients to the average change observed in their respective neighborhoods.

```
ggplot(prop_assess, aes(x = TaxYear, y = pct_chg, color = value)) +
  geom_line(linewidth = 1) +
  facet_wrap(~NAME) +
  scale_y_continuous(labels = label_percent()) +
  scale_color_hda() +
  theme_hda() +
  theme(legend.position = "top",
        axis.text.x = element_text(angle = 90)) +
  add_zero_line("y") +
  labs(title = "Value of DPL client homes versus surrounding neighborhoods",
       subtitle = "Percent change in assessed value from 2017 to 2022",
       caption = "**Notes:** Homes sold to clients in 2017. Neighborhood average derived f
```



The plot on the left shows a client's home they purchased in Fifeville in 2017 increasing in total assessed value by almost 50 percent by 2022, compared to a neighborhood average increase of 38 percent.

The plot on the right shows the same for a home purchased by a client in The Meadows. In this case, the assessed value of the client's home almost doubled (76 percent) in the first year following their closing, likely due to the city assessor making a major adjustment following the sale of this home. (It was assessed for $104,500 in 2017, but sold for $178,700.) Since 2018, the home's value has increased in close pace with its surrounding