The Socioeconomic Consequences of the Decline in Small Mortgages

An Investigation into Three Cities: Philadelphia, El Paso, and St. Louis

A Quantitative Analysis

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Disclaimer: *The Pew Charitable Trusts provided funding for this project, but Pew is not responsible for errors in this white paper and does not necessarily endorse its findings or conclusions.*

I. Introduction and Executive Summary

A. Motivation of report

Most cities in the United States experience a wide range of household prosperity, income, and wealth within their boundaries. In many cases, areas of low income and affluence are concentrated in completely different areas of the city, with few economic crosscurrents. As a result, low-income areas can become mired in slow or stagnant growth relative to the high-income areas, playing a role in the long-term and persistent wealth gaps between these groups, according to a 2014 Brookings report.

There are many reasons. In some cases, public transportation doesn't connect people to jobs. In addition, for those families with modest incomes desiring to own a home and build wealth, there is an "acute shortage" of homes for sale, a result of restrictive land use and zoning practices, according to a 2021 Harvard report (p. 11).

The primary goal of this report is to investigate another key challenge: the increasing difficulty for individuals and families with modest incomes to secure financing for inexpensive homes, even though they are qualified buyers. Fewer banks are offering financing for so-called small-dollar homes, which we define as costing less than $150,000, following the lead of The Pew Charitable Trusts' most recent research on this issue.

That leaves out thousands, if not millions, of potential U.S. homeowners from acquiring these properties. As a report by New America points out, "homeownership is a key component of building wealth in the United States: The average homeowner boasts a net worth of $255,000, close to 40 times that of the average renter ($6,300)." Without mortgage financing available at the lower end of the market, New America finds that investors are increasingly purchasing these lower-end homes with cash.

A unique focus of this research is to investigate to what extent these national trends play out in American cities. We explore three distinct cities that have many of these socioeconomic divisions: Philadelphia, Pennsylvania; El Paso, Texas; and St. Louis, Missouri. Within each city, we use statistical and mapping techniques to designate neighborhoods as "Distressed," "Affluent," and "All Other."

This framework acknowledges that economic development within a particular urban area is far from uniform, especially when contrasting high-distress areas with affluent ones. We find that one-size-fits-all housing policies may be inappropriate if an area of a city labeled as "Distressed" has housing and economic trends that are completely in contrast to areas labeled as "Affluent."

B. Brief summary of research findings

Below are important findings that stem from our research, which we elaborate on in more detail in Section III, using maps and figures to illustrate.

- As of 2022, there were still large numbers of owner-occupied homes assessed at $150,000 or less in each of the three cities, particularly in Distressed areas. However, the stock of low-cost homes declined from 2007 to 2022 due to home price appreciation.[1]
- After the Great Recession, applications for and originations of small-dollar mortgages dropped more dramatically than the stock of small-dollar homes valued at $150,000 or less. These trends were more severe in Distressed areas of Philadelphia and St. Louis, but less severe in Distressed areas of El Paso.
- Between 2007 and 2022, Distressed areas saw consistently higher levels of all-cash purchases than Affluent areas despite residents there having lower incomes and less wealth than the city as a whole. This finding suggests that investors are more active in these markets. Consistent with this finding, rental housing began to account for an increasingly large share of total occupied housing units in each of the three cities during the study period.
- Nominal housing prices rose in nearly all Affluent and Distressed areas between 2007 and 2022. But while price growth in Affluent areas was consistent across cities, price growth in Distressed areas varied widely, from -4 percent in St. Louis to 175 percent in El Paso.
- Distressed communities in Philadelphia and El Paso experienced a rapid rise in housing unaffordability between 2007 and 2022 as income growth lagged housing price growth. In contrast, Affluent areas in these cities are becoming more affordable using the same index.
- In all three cities, commute times to work are higher for residents of Distressed communities than residents of Affluent communities, making it more difficult to earn the income necessary to afford a home purchase.

[1] Property values come from the American Community Survey and are "owner-assessed," which means they represent an owner's subjective valuation of their property. Although these valuations are often correlated with market values or valuations established by commercial assessors, they may deviate substantially from those values.

- Since 2017, technology access has sharply improved for residents of Distressed communities, which can help residents better connect with opportunities in the housing market. Also, educational attainment is improving for residents of Distressed communities, which can help link them to better jobs and potentially higher incomes.

C. Outline of report

In Section II, we discuss the methodology used to complete the data analysis. We first discuss the rationale for choosing the three U.S. cities highlighted in this report. Next, we describe the three primary datasets that underlie the analysis and explain how they were merged to create a larger dataset from 2007 to 2022. (Far more detail of that involved process is discussed in Appendix A.) We then explain the methodology for our prosperity index, which is based on average poverty rates and share of housing units assessed at under $150,000. This index is used to define Distressed and Affluent areas of each city.

In Section III, we present and discuss the nine main findings of this analysis, using graphs to illustrate notable patterns in small-dollar mortgage availability, affordability, the influx of all-cash buyers, changes in renting vs. buying, and other socioeconomic trends. Notably, the breakdown by the designated economic area yields insights that an overall city analysis would miss.

Section IV presents overall conclusions from this project and summarizes the key findings. It uses those findings to build a case for how one-size-fits-all public policies may miss important trends if specific neighborhood trends are not analyzed separately. What policies may work for an affluent community may be completely inappropriate for a community in high economic distress, even if in both cases small-dollar homes are the point of focus. This report's method of investigating and analyzing cities as having distinct neighborhood housing markets provides a key argument for flexible government housing policies tailored around the needs of specific geographic and socioeconomic areas. Last, we provide policy suggestions, limitations of the research, and suggestions for future research.

Appendix A gives a more in-depth methodology of the way the three datasets were merged and explains how census tracts are defined over time. Appendices B, C, and D provide more detailed data for El Paso, Philadelphia, and St. Louis. A full account of all the socioeconomic variables from the ACS, HMDA, and CoreLogic datasets is included, reporting on changes in a multitude of housing and socioeconomic variables, comparing 2007 to 2022, broken down by our definitions of Distressed, Affluent, and All Other neighborhoods. Appendix E provides additional maps on population, income, and loan applications for each city for informational purposes. Last, Appendix F provides an example of how these findings help to challenge basic assumptions about the small-dollar housing stock, mortgage markets, and economic growth, using St. Louis as an example.

II. Data and Methodological Overview

A. Rationale for choosing the three cities

The Pew Charitable Trusts selected the cities included in this report after a review of national data on mortgage origination trends. Using data from the Home Mortgage Disclosure Act (HMDA), Pew identified metropolitan areas where the inflation-adjusted decline in small mortgage originations exceeded the national average between 2004 and 2021. Pew adjusted for inflation using the Zillow Home Value Index (ZHVI) for each metropolitan area.

From the group of metropolitan areas with a steep decline in small mortgage originations, Pew gave preference to areas whose central city population exceeds 250,000 residents. This was done to ensure that researchers would be able to find enough interviewees for the qualitative portion of this analysis. Pew also sought out cities in geographically different parts of the country, ultimately selecting one in the Northeast, one in the Midwest, and one in the Southwest. Pew chose Philadelphia, St. Louis, and El Paso, respectively.

B. Brief description of the three city datasets

Our goal with this project was to merge data from the American Community Survey, CoreLogic, and HMDA at the census tract level rather than a county approach for each chosen city. This more granular level of data is necessary to investigate trends and comparisons for our designated areas of the city, because in this report groups of census tracts are pieced together to form comparison units, that is, designated areas of Distressed, Affluent, and All Other income. However, because census tracts sometimes change their borders over time, this presented additional potential problems which we tackled using a process described in Appendix A to facilitate the merge. We included the years 2007-2022 where possible, as that allowed us to study pre- and post-Great Recession years (2008-2010), since a number of banking regulations occurred in its wake that have affected small-dollar mortgages.

1) American Community Survey

The U.S. Census Bureau's American Community Survey (ACS) does five-year demographic surveys that are administered by the U.S. Census Bureau. The data is freely available for the years 2009 to 2022. For the years 2007 and 2008, we estimate using a simple linear model based on later years. Owner-assessed housing prices come from the ACS, with more detail on those estimates provided in Appendix A, along with a host of socioeconomic variables at the census tract level.

2) CoreLogic

CoreLogic data provides nationwide real estate transaction and property-related data. CoreLogic Inc. is a for-profit database management company that provides financial, property, and consumer information, analytics, and business intelligence. The datasets and products created by CoreLogic are of excellent quality, validated not only by CoreLogic's team of data scientists, but also by their team of economists, who specifically validate data from the perspective of researchers. An additional benefit of CoreLogic has to do with tracking investor activity. CoreLogic provides data on all home transactions, regardless of whether the purchase was made with a mortgage or completed with cash only. We purchased the data for use for the years 2007-2022 for the three cities under study.

3) Home Mortgage Disclosure Act

Home Mortgage Disclosure Act (HMDA) data is loan application-level data on mortgages reported by eligible lending institutions. Data is freely available for the years 2007-2022. Home mortgage data comes from HMDA to analyze trends in mortgage loan applications, denials, and origination levels and rates. Data was also used to analyze trends regarding home improvement loans.

C. Overview of merged dataset

In order to complete the analyses by census tract, the data from all three sources must be merged at the level of the census tract-year. One issue is whether the census tracts have the same shape at the same time frame. For example, in the ACS data, the year 2009 uses 2000 census tract boundaries. For the years 2010-2019, it uses the 2010 boundaries. For the years 2020 and 2021, it uses the 2020 boundaries. In the HMDA data, similar challenges occur regarding changing boundaries, which are outlined in the supplemental section. In the CoreLogic data, the census tract identifiers follow the 2020 boundaries, so there are fewer challenges. To overcome these hurdles, the census tracts need to be standardized, so that a merge can create the unit of observation, which is the census tract-year. For the census tracts that change borders over time, the process of creating a standardized measurement for a merged dataset is reported in much greater detail in Appendix A.

D. Other challenges with the data

Other challenges include that HMDA data is not uniformly collected across all institutions, which could result in unrepresentative estimates. This stems from 2018 federal legislation that exempted certain smaller lending institutions and credit unions from reporting all data, in what is known as a partial exemption. However, according to a 2021 GAO report, HMDA data still captures almost 90 percent of all lending data. The lenders that do qualify for exemptions account for a small amount of all loans, according to the report. This means our statistical findings will be fairly robust along these lines.

The quality of the data is very high. There are very few cases that have missing data with an associated census tract in either CoreLogic or HMDA data. Our records indicate 0.01 percent or fewer cases are missing records, on average, between 2007 and 2022 in HMDA data with originated purchase loans for primary residences. There is sometimes miscoded or misaligned information. In one case a decimal system is used, and in another FIPS codes are used. These must be reformatted to make them consistent.

Our CoreLogic and HMDA data range from 2007 to 2022, but our ACS data ranges only from 2009 to 2022, since we use the last year in the five-year range as the representative year. To backfill the tract-level series, we linearly extrapolated the trends where necessary.

Regarding demographic definitions of race, the classification of who is White and who is Black has remained stable over time, even as other racial classifications have broadened, such as Asian categories. Thus, we do not expect methodological problems around racial classification at the level of the census tract.

Last, the COVID-19 pandemic may present some challenges in both direct behavioral changes and impact on data collection and surveying. These two potential issues could impact our data in unforeseen ways. Drops in lending during the pandemic may be affected along socioeconomic lines that are unrelated to a regulatory environment. However, the vast majority of years in this dataset occurred prior to these two years.

E. Summary of key housing data and sources

Since we obtain information on housing data from different sources for use in our analysis, here is a quick summary of where each of the important variables is found and a summary description:

Table 1.

Description of variables	Data source
Owner-assessed housing values, by year and census tract	American Community Survey 5-Year Population Estimates
Average nominal sales price of houses, by census tract and year Whether a purchase was made using cash or a mortgage, by census tract and year	CoreLogic
Mortgage applications, originations, and denials, by census tract and year	Home Mortgage Disclosure Act

F. Selecting designated areas of comparison

1) Creation of prosperity index with maps for each city

We categorized sections of each city into three categories. The first category designates the city's Distressed Area, the second designates the Affluent Area, and the third category contains the remainder of the city, or All Other Income. The following steps were taken: Using ACS data, the poverty rate and the percentage of homes assessed under $150,000 were averaged in order to create a simple prosperity index that varied by the census tract using the formula below:

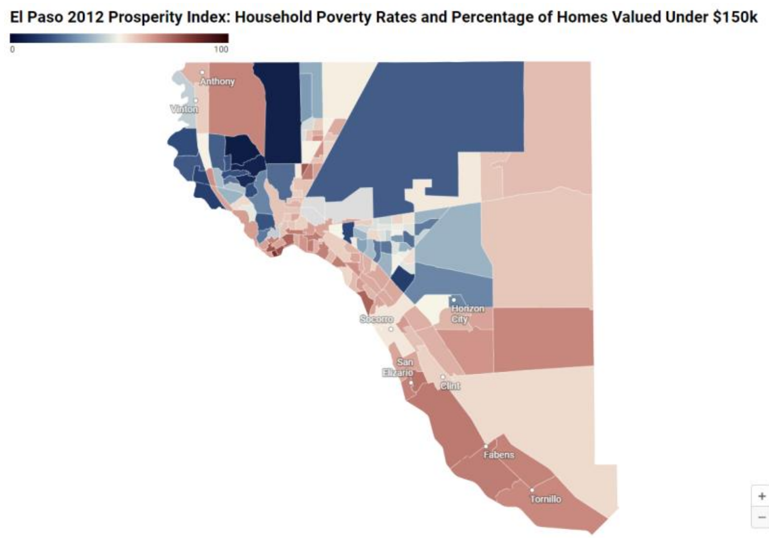
For each census tract in the year 2012,

$$\text{Prosperity Index} = \frac{\text{(Poverty rate + Percentage of homes assessed under \$150,000)}}{2}$$

The year 2012 was chosen because it marks a decade earlier than the end of the time-series data (2022) for this project and served as a good baseline for choosing the designated areas. The reason for using both of these variables was to capture both the state of the housing market as well as the level of income in the area. Potentially, there could be an area with low income, such as retirees, but where residents were not in poverty. In practice, we examined Datawrapper maps with each variable separately and found a very high level of correlation between the two.

Using the prosperity index, we created a Datawrapper map[2] for each of the three cities in order to investigate and decide upon the designated comparison areas. As seen on the maps below, dark blue signified higher prosperity (both lower poverty and more expensive homes), whereas dark red was lower prosperity (higher poverty and less expensive homes). Intermediate areas had a mix of more neutral tones.

Figure 1.

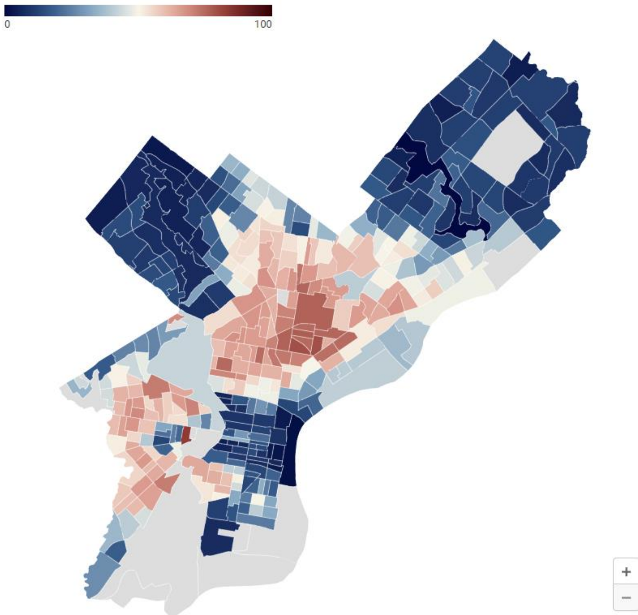


Note: Higher prosperity is darker blue and lower prosperity is darker red.
https://www.datawrapper.de/_/idwB7/

[2] Datawrapper is a free proprietary software that enables creative visualization using trendlines, maps, and scatterplots. We used it throughout this report to clearly explicate trends among and within cities far better than traditional charts used by Excel or other statistical software. The software is found at datawrapper.de. Data for these maps comes from American Community Survey (ACS) 2012 5-year estimates.

Figure 2.

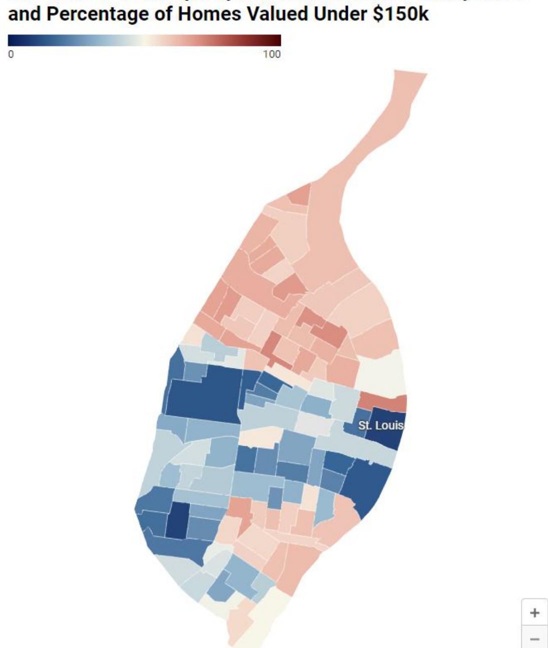
Philadelphia 2012 Prosperity Index; Household Poverty Rates and Percentage of Homes Valued Under $150k



Note: Higher prosperity is darker blue and lower prosperity is darker red.
https://www.datawrapper.de/_/9JPQ9/

Figure 3.

St. Louis 2012 Prosperity Index. Household Poverty Rates and Percentage of Homes Valued Under $150k

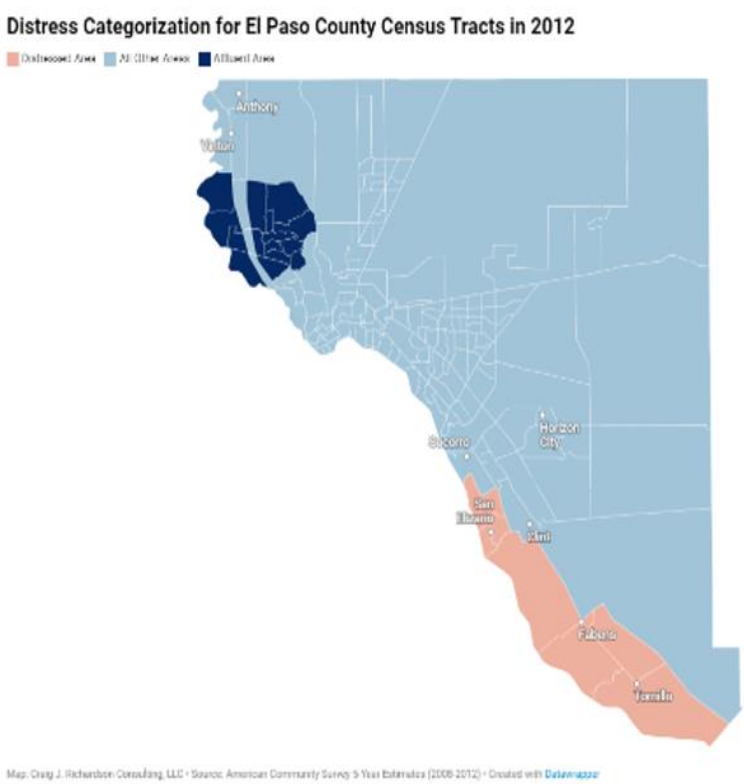


Note: Higher prosperity is darker blue and lower prosperity is darker red.
https://www.datawrapper.de/_/o5Cic/

2) Formulation of contiguous areas based on prosperity index

In conjunction with the Pew Charitable Trusts team, contiguous areas within each city were selected to represent the following comparison zones: Distressed, Affluent, and All Other. The new areas were uniformly color-coded in three solid colors, as opposed to the continuous values and colors generated by the prosperity index. Contiguous areas of mostly red (high poverty) and mostly blue (affluent) were the central comparison groups in each city. These maps are seen below. All other tracts (those that were not designated Distressed nor Affluent) were placed into the category of All Other. Those three discrete categories were then coded in our dataset for each census tract, serving as the crux for the analysis that would follow for graphs and tables.

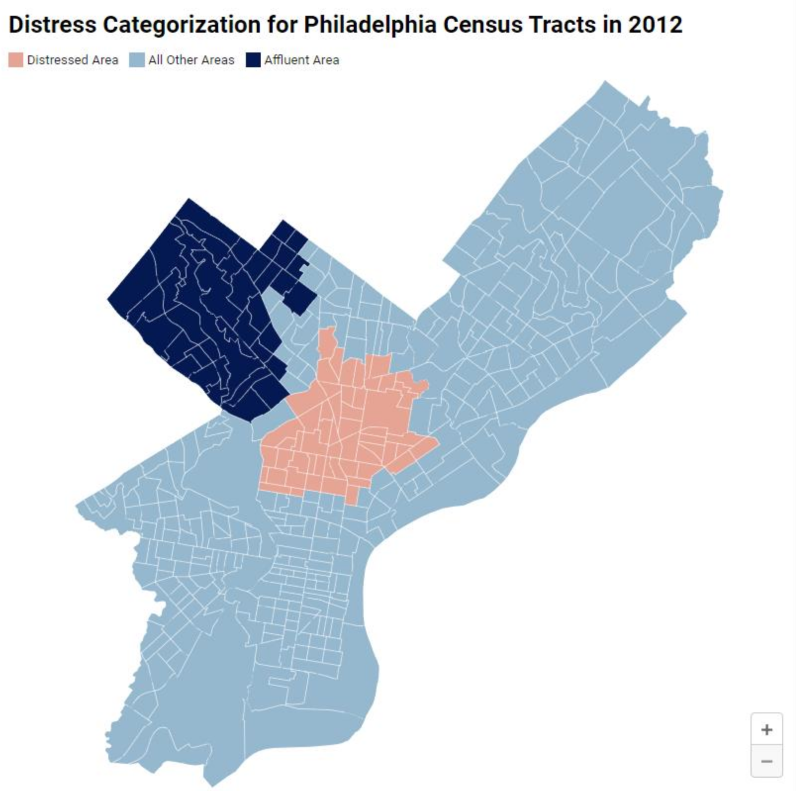
Figure 4. El Paso category map for report analysis



https://datawrapper.dwcdn.net/0b0Ug/9/

Note for statistical categories: Distressed (light red), Affluent (dark blue) and All Other (light blue)

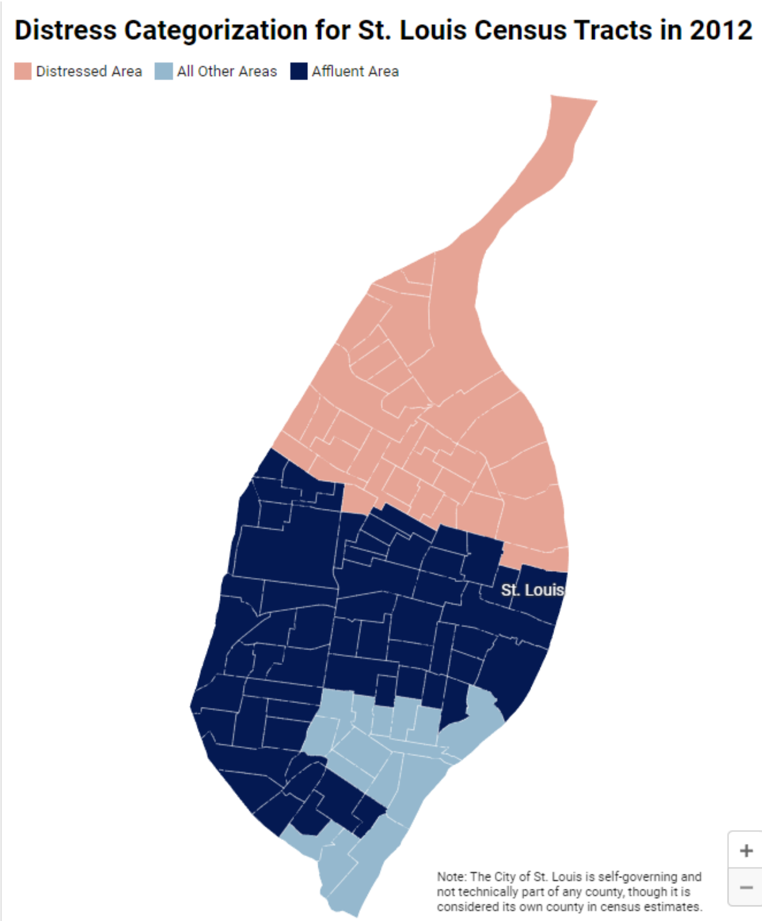
Figure 5. Philadelphia category map for report analysis



https://www.datawrapper.de/_/Qrhwc/?v=8

Note for statistical categories: Distressed (light red), Affluent (dark blue) and All Other (light blue)

Figure 6. St. Louis category map for report analysis



https://www.datawrapper.de/_/wqoun/

Note for statistical categories: Distressed (light red), Affluent (dark blue) and All Other (light blue)

III. Key Findings from Philadelphia, El Paso, and St. Louis

This section identifies significant trends and patterns that potentially link a drop in accessibility to small-dollar mortgages between 2007 and 2022 to an increase in all-cash purchases and a subsequent drop in the amount of owner-occupied housing. Note this is a descriptive, not a causal, analysis. In addition, despite home prices appreciating over the years, there are still large numbers of small-dollar homes (defined as an assessed value of less than $150,000 for this project) across all three cities.

Using the methodology discussed earlier, we segment these statistical trends based on different areas of the city that we identified as “Distressed,” “Affluent,” and “All Other” areas in the maps described above. We also track nominal housing prices over time, identifying significantly different trends based on the area. We have also created an affordability index that indicates the approximate time needed to buy an average-priced house for sale at prevailing wages within each segment of the respective city. We find that each of the three cities has a unique story to tell, yet there are significant underlying trends that speak to rising difficulty in access to small-dollar mortgages, particularly in the most distressed areas of the cities.

In addition, we track some interesting trends across the three cities with regard to technology access and education, again segmenting by the designated areas of the city. We find heartening trends in improved technology access in the most distressed areas, along with a lower stock of residents with less than a high school education.

Here are nine findings from this analysis that are most striking, though dozens of other variables remain of interest that are reported later in Appendices B, C, and D for El Paso, Philadelphia, and St. Louis, respectively. Live links to the Datawrapper figures are also included.

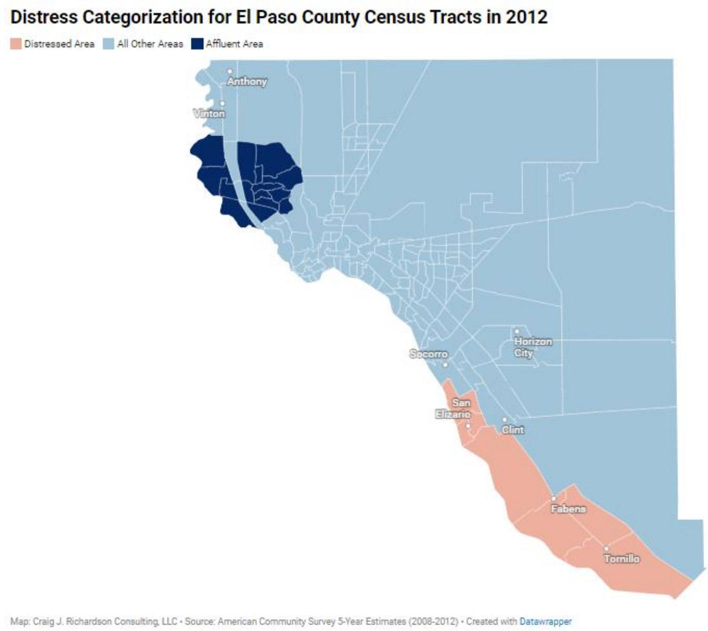
A. Plenty of owner-occupied small-dollar homes remain, with a high concentration in Distressed areas of each city.

Despite rising home prices across the country in recent years, in 2022 there were still plenty of owner-occupied small-dollar homes assessed at $150,000 or less in these three urban areas.[3]

As seen in the maps below, there is a marked correspondence between areas of distress and areas with a high concentration of sub-$150,000 homes. Distressed areas are marked in a peach color in the first map. The second map shows the concentration of small-dollar (sub-$150,000) homes, and darker blue areas denote an increasing concentration of these homes. For Philadelphia and particularly St. Louis, the two areas jump out as highly correlated and distinct from the rest of the city.

[3] Note that for these properties, the values come from the American Community Survey and are owner-assessed. Thus, they represent a subjective value that is highly correlated with market values or commercial assessors’ values, but may deviate from those values.

Figure 7. Comparisons of distress categorizations to owner-occupied housing stock under $150,000 for El Paso, Philadelphia, and St. Louis.



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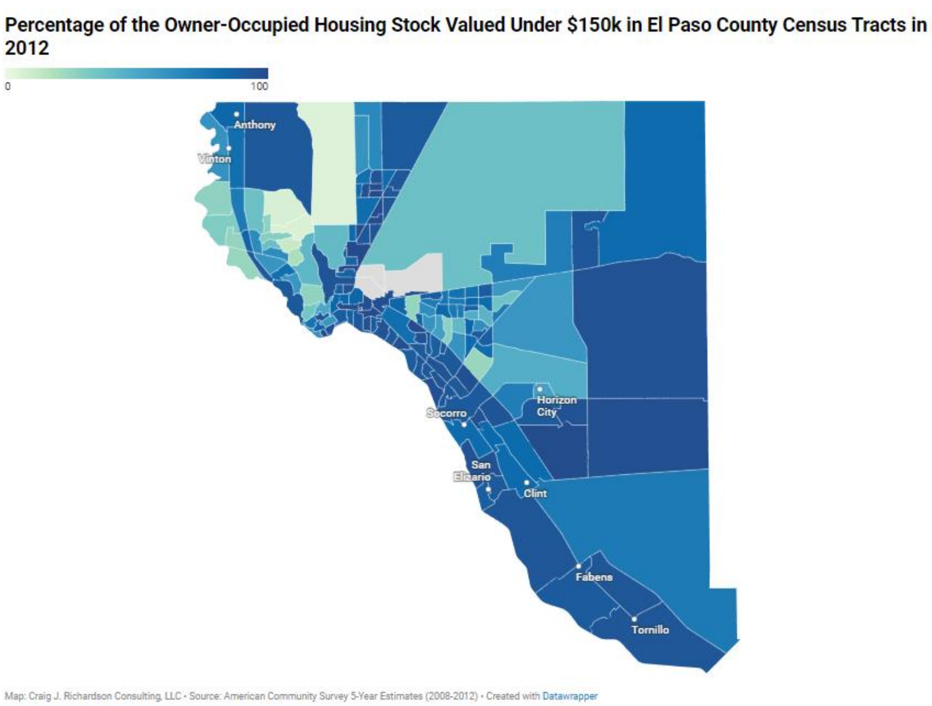

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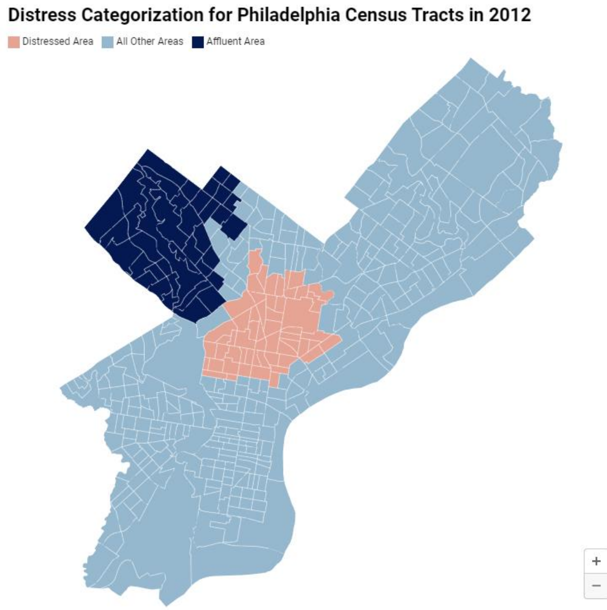

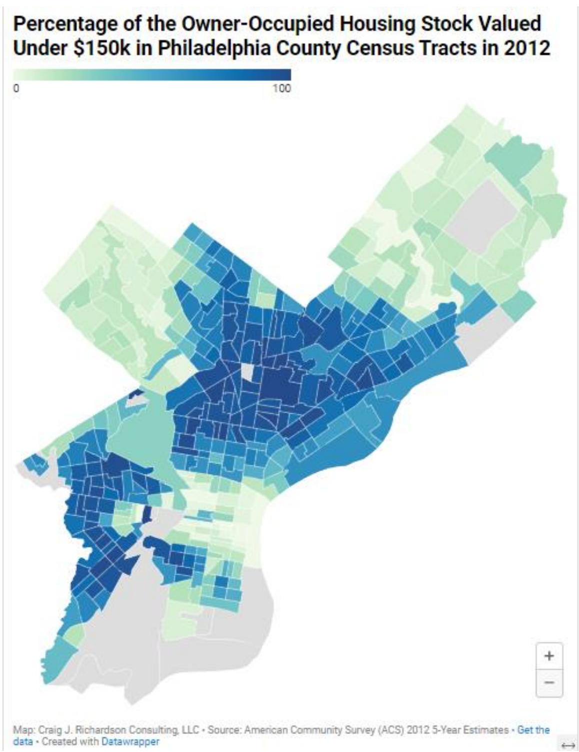

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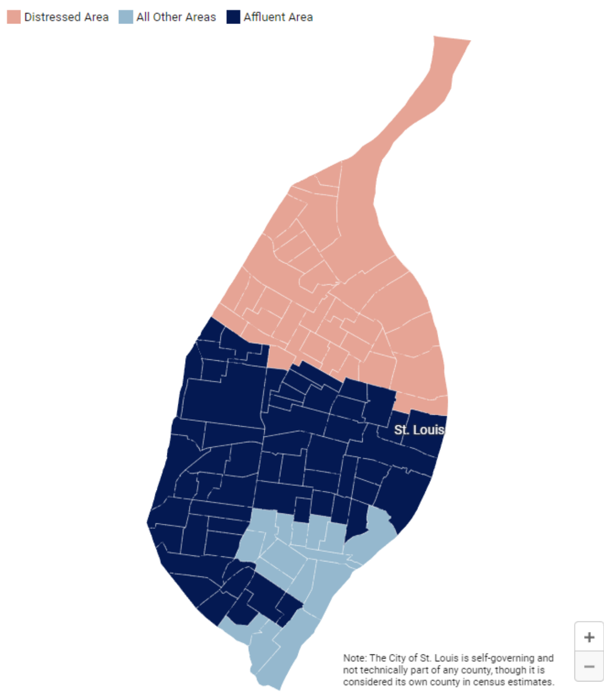
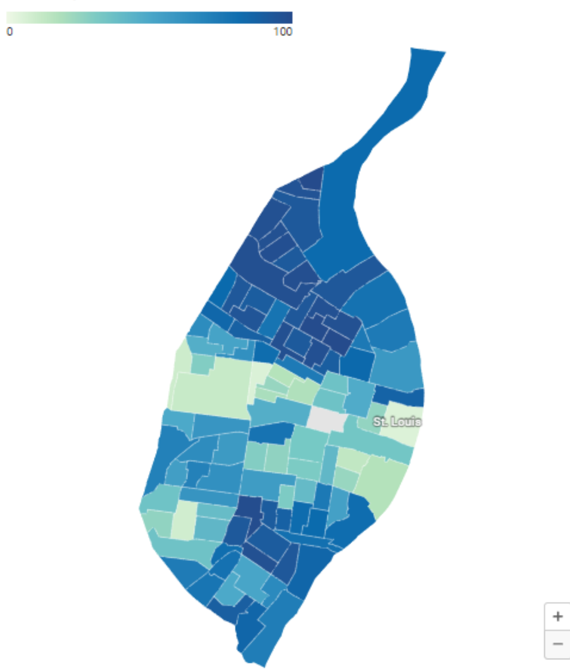
Distress Categorization for St. Louis Census Tracts in 2012



Percentage of the Owner-Occupied Housing Stock Valued Under $150k in St. Louis Census Tracts in 2012



Map: Craig J. Richardson Consulting, LLC • Source: American Community Survey (ACS) 2012 5-Year Estimates • Get the data • Created with Datawrapper

https://www.datawrapper.de/_/StIRe/

B. After the Great Recession of 2008-10, small-dollar mortgage applications and originations dropped dramatically. The severity of the trends was generally higher in Distressed areas of Philadelphia and St. Louis.

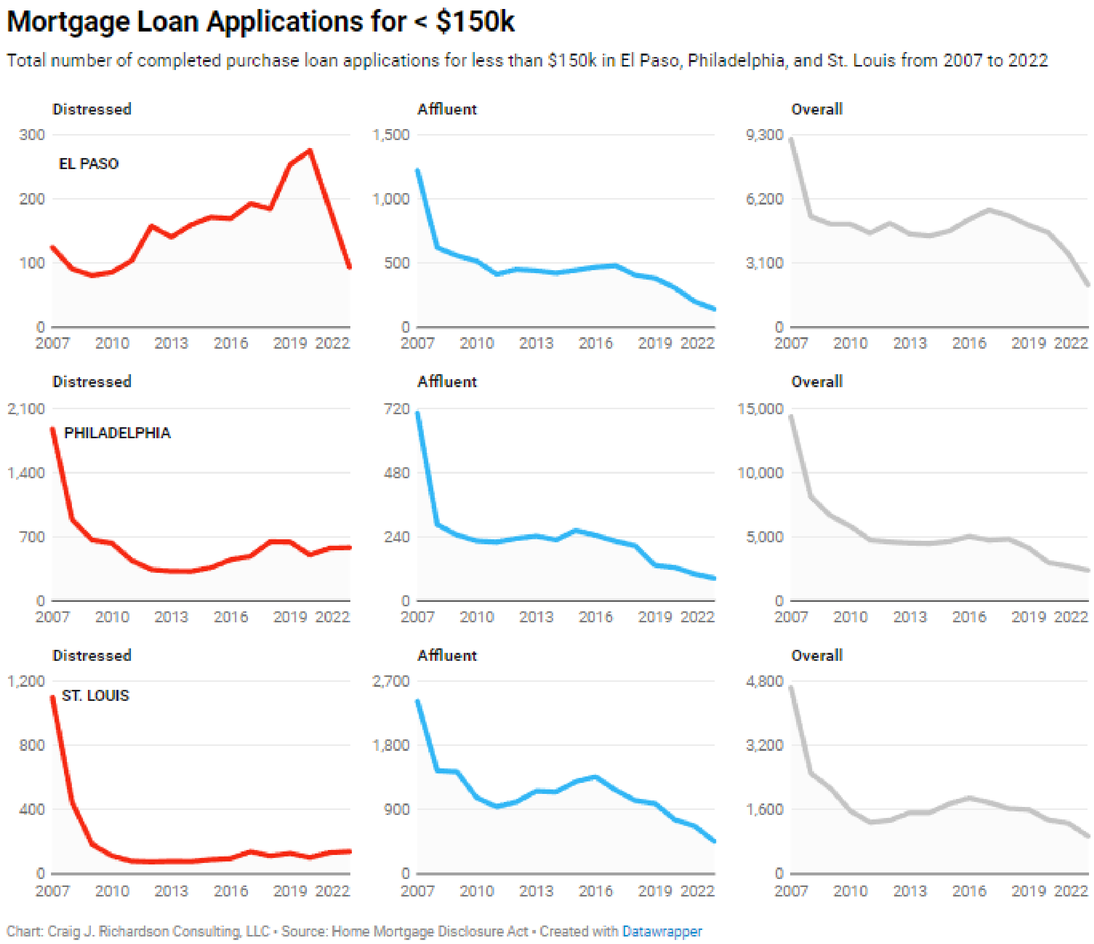
With the exception of El Paso's Distressed areas, applications and originations for small-dollar mortgages experienced a severe drop across all three cities' designated areas since 2007 and have never recovered since the 2008-10 Great Recession. Focusing on Philadelphia and St. Louis, Distressed areas exhibited severe drops in mortgage loan applications, with St. Louis falling close to zero by 2010. In Affluent areas, these small-dollar mortgage loans dropped by about half to two-thirds by 2009, but after that remained more or less steady until 2016. After 2016, small-dollar mortgage applications began trending downward again in Affluent areas, perhaps this time driven by steady housing appreciation that made $150,000 homes more scarce.

One potential reason for the sharp drop in small-dollar lending is that the 2010 Dodd-Frank Act's new banking regulations have been documented to make small-dollar mortgages relatively more expensive to process than larger loans. This is due to a rise in fixed processing costs per loan and caps on banking fees for smaller loans. For many banks, these smaller loans are not worth the effort to issue. Other evidence suggests that low-cost homes are more likely to have structural deficiencies that result in higher loan denial rates and that sellers prefer all-cash buyers. It is not yet known why only El Paso's Distressed area had the opposite trend until 2020, but the small number of mortgages in each tract could quickly change if there was rapid gentrification or neighborhood investment.

Post-2010, those downward trends may have accelerated in Distressed areas if poverty was also becoming increasingly concentrated, a trend that has been documented by the Brookings Institution to be a national trend across many cities, leading to more homes falling into disrepair and thus being less likely to be attractive to lenders. Particularly in St. Louis, where nominal housing prices have been falling over the study period (see III.D), this is a likely bellwether for increasing concentration of poverty.

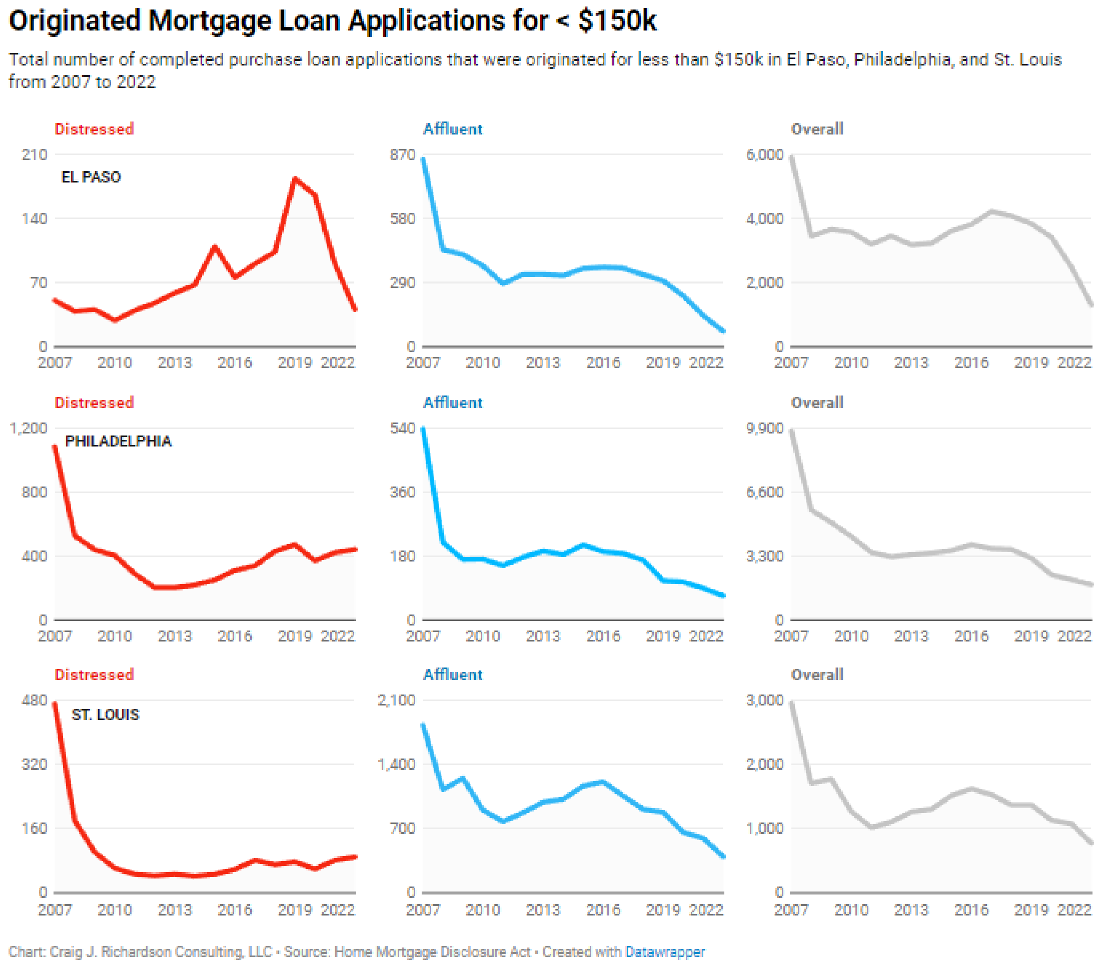
Mortgage denials have followed a similar trend. This latter trend could be occurring because of potential applicants being steered or dissuaded from applying unless they have particularly strong credit histories or additional help with financing. Since a mortgage denial reflects lost resources of time and money on the part of lending institutions, they have incentives to keep denial rates as low as possible. Lending practices tend to evolve over time as banks acquire new ways to assess risk on the part of traditionally higher-risk applicants. This finding is consistent with earlier research that demonstrated that real denial rates are higher for small-dollar mortgages.

Figure 8. Small-dollar mortgage applications in Affluent and Distressed areas



https://www.datawrapper.de/_/y4lV2/

Figure 9. Small-dollar mortgage originations in Affluent and Distressed areas



https://datawrapper.dwcdn.net/PAenu/3/

Figure 10. Small-dollar mortgage denials in Affluent and Distressed areas

Denied Mortgage Loan Applications for < $150k

Total number of completed purchase loan applications that were denied for less than $150k in El Paso, Philadelphia, and St. Louis from 2007 to 2022

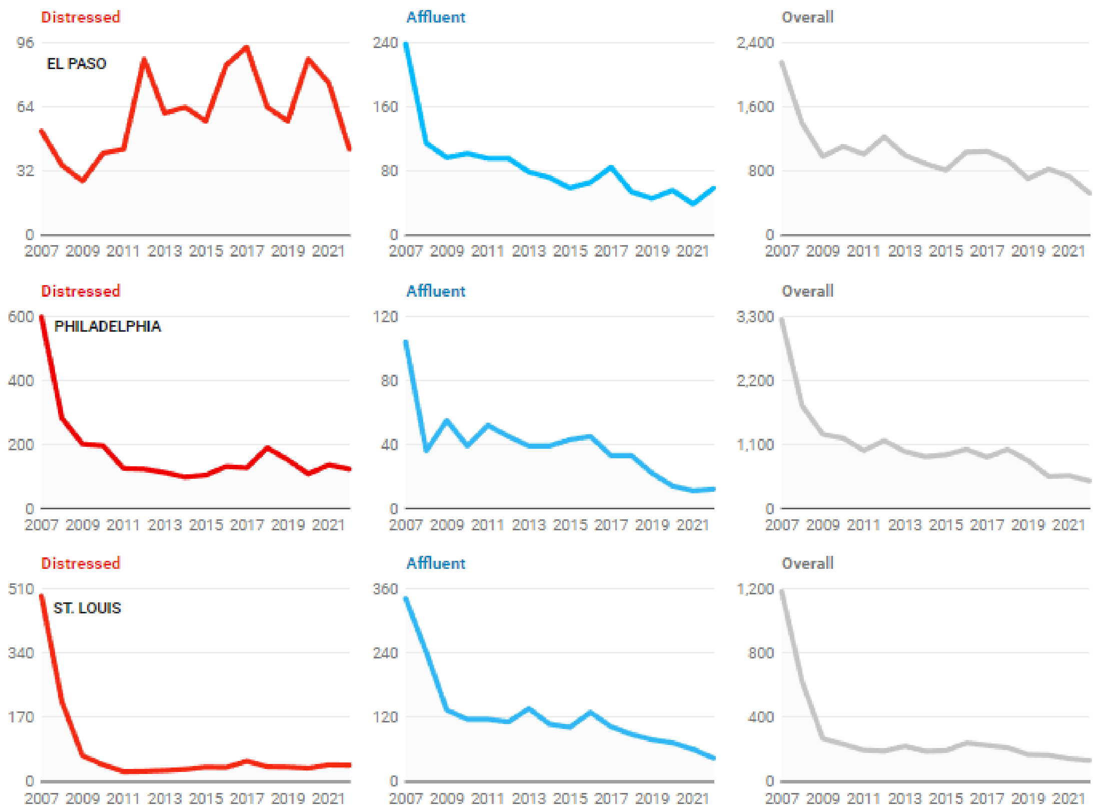


Chart: Craig J. Richardson Consulting, LLC • Source: Home Mortgage Disclosure Act • Created with Datawrapper

https://datawrapper.dwcdn.net/yrygK/2/

C. Distressed areas see consistently higher levels of all-cash buyers than Affluent areas, particularly in St. Louis.

Between 2009 and 2019, originations for small-dollar mortgages across the U.S. fell precipitously. Those loans between $10,000 and $70,000 dropped by 38 percent and loans between $70,000 and $150,000 fell 26 percent. In contrast, originations for loans exceeding $150,000 rose by 65 percent. Three-quarters of homes costing more than $100,000 were purchased with the help of a mortgage loan in 2019, whereas only 23 percent of homes below $100,000 were purchased with a mortgage loan. In many cases, investors and all-cash buyers purchase and flip these homes for a profit or use them for rental income. Our data on Philadelphia and St. Louis underscores that trend where Distressed areas, dominated by homes assessed at $150,000 and below, are seeing the largest trends toward all-cash purchases.

This suggests stark differences in lending opportunities for applicants based on socioeconomic status and wealth. In addition, in Philadelphia and St. Louis the trends are widening over time, while remaining constant in El Paso. Little change in financing has occurred in the Affluent areas, suggesting that access to financing options differs according to mortgage size, socioeconomic status, and wealth. In El Paso, there was little change in the trend, though the levels of purchases with cash are higher in Distressed areas.

Distressed areas have more small-dollar homes, and the increase in all-cash purchases is likely a response to the increased regulatory costs and lower lender profits on small-dollar mortgages, as discussed earlier. The largest increase has occurred in St. Louis, which has moved to nearly exclusively cash purchases in Distressed areas of the city. Notably, St. Louis has the most severe demarcation between the Affluent and Distressed areas of the city, as seen previously in Section II, C (p. 13).

Figure 11: El Paso.

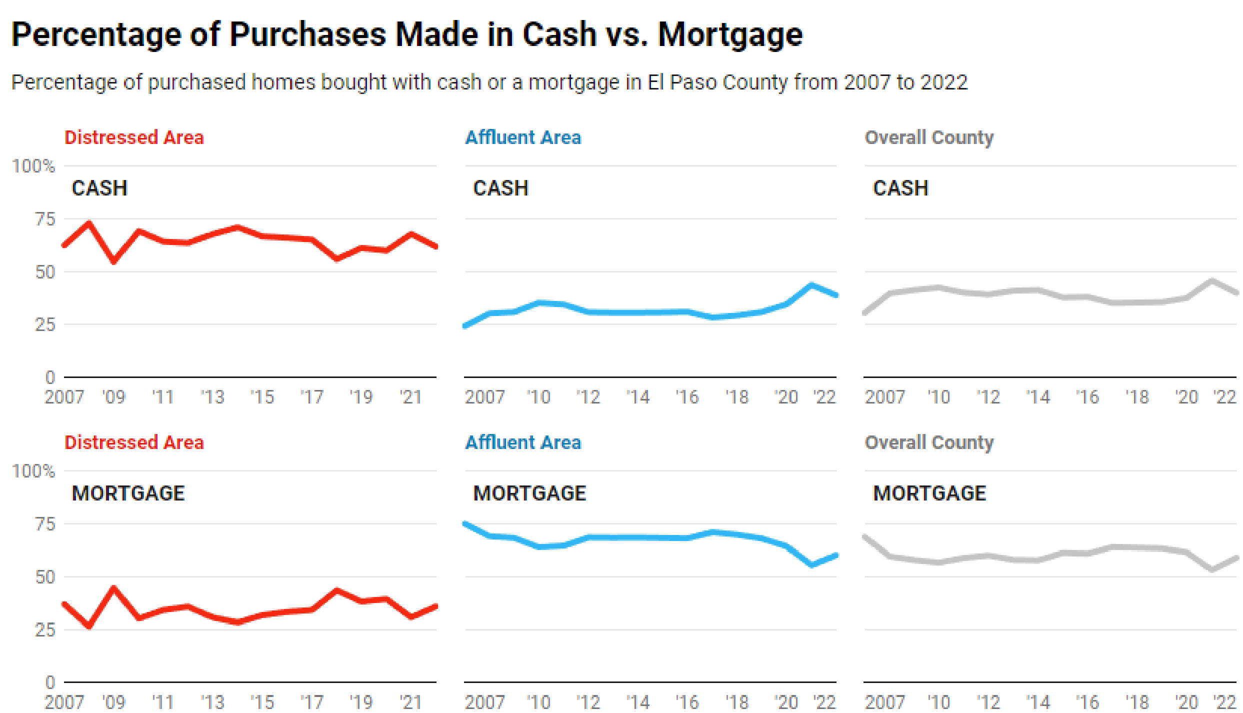


Figure 12: Philadelphia.

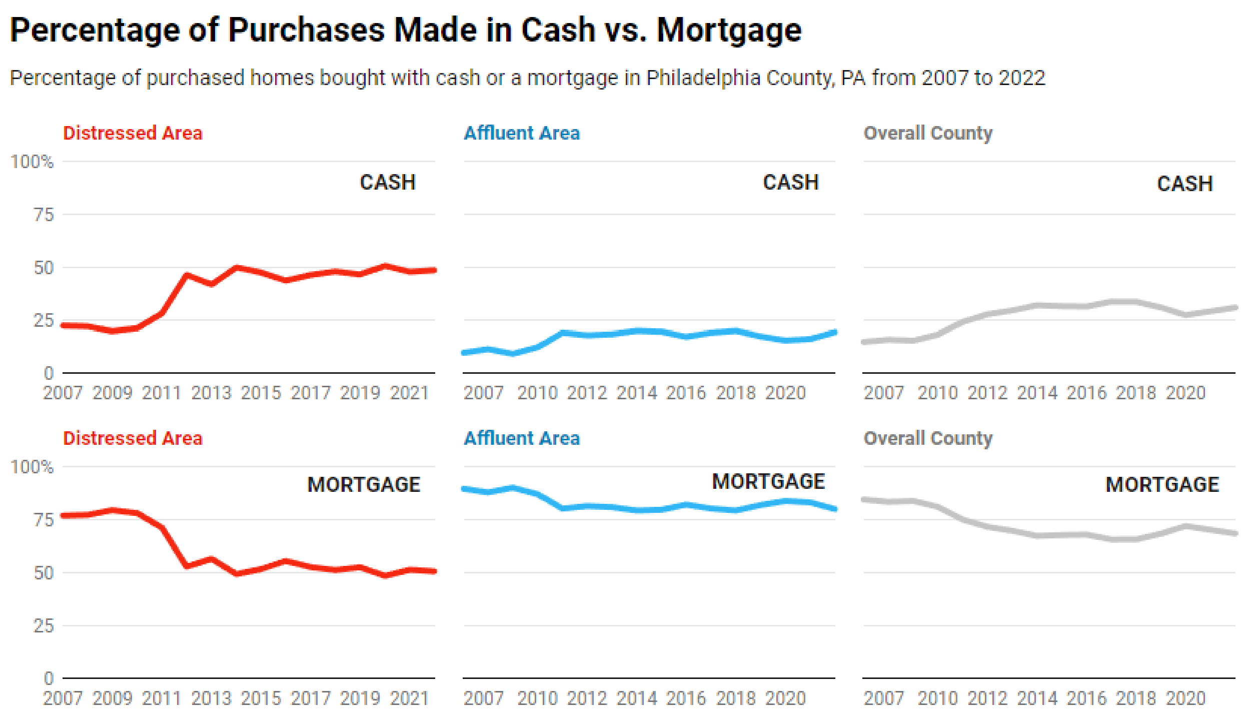
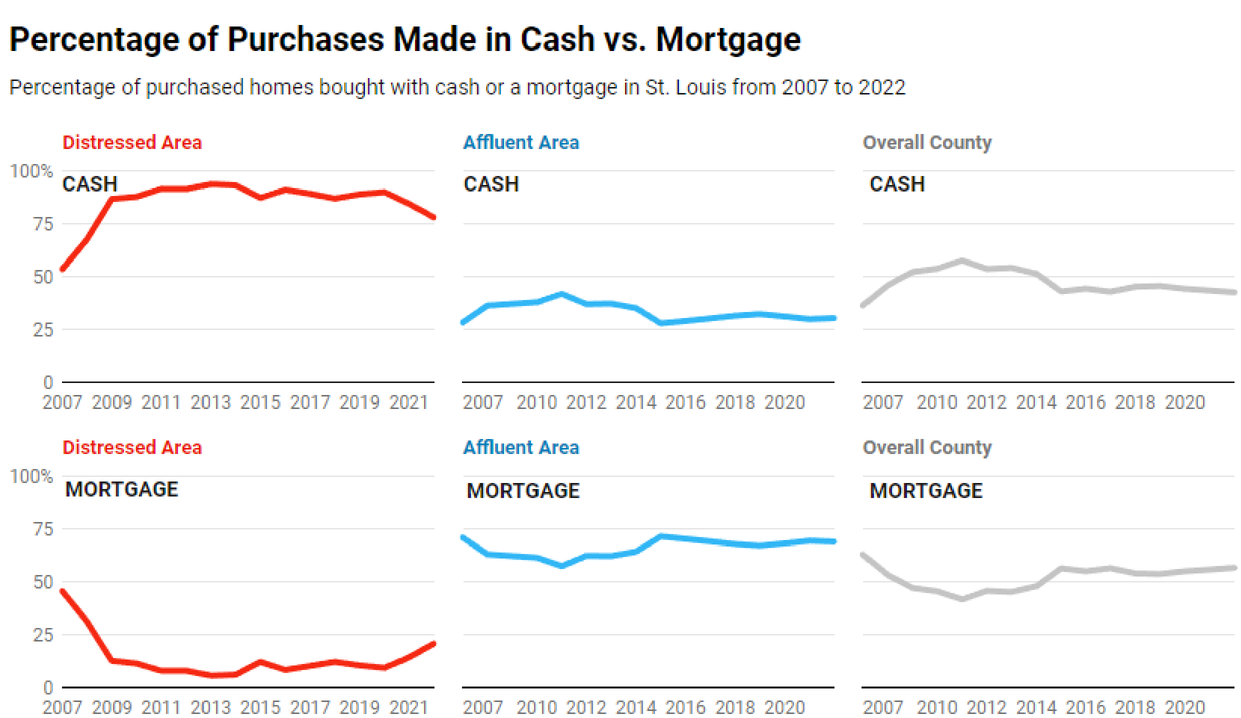


Figure 13: St. Louis.



D. Owner-occupied housing under $150,000 is becoming less common.

Not surprisingly, with the increase in cash-financed purchases of small-dollar homes, owner-occupied housing in the lowest price range (self-assessed at less than $150,000) is falling steadily since 2007, driven by home appreciation as well as greater difficulties in mortgage financing in this price range, as seen previously. Despite having large numbers of homes in the sub-$150,000 range in 2022, all three cities have seen notable drops in this range of owner-occupied homes between 2007 and 2022. The steepness of these drops also varies by whether it is Affluent or Distressed. El Paso's Affluent area saw dramatic drops, with less than 20 percent of its housing stock in the sub-$150,000 range by 2022, compared to nearly 50 percent in 2007. Similar trends occurred for Philadelphia and St. Louis in the affluent areas. Distressed areas in all three cities saw less steep declines, and all had 50 percent or more of the housing stock valued at $150,000 or below by 2022.

Figure 14. El Paso, Philadelphia and St. Louis

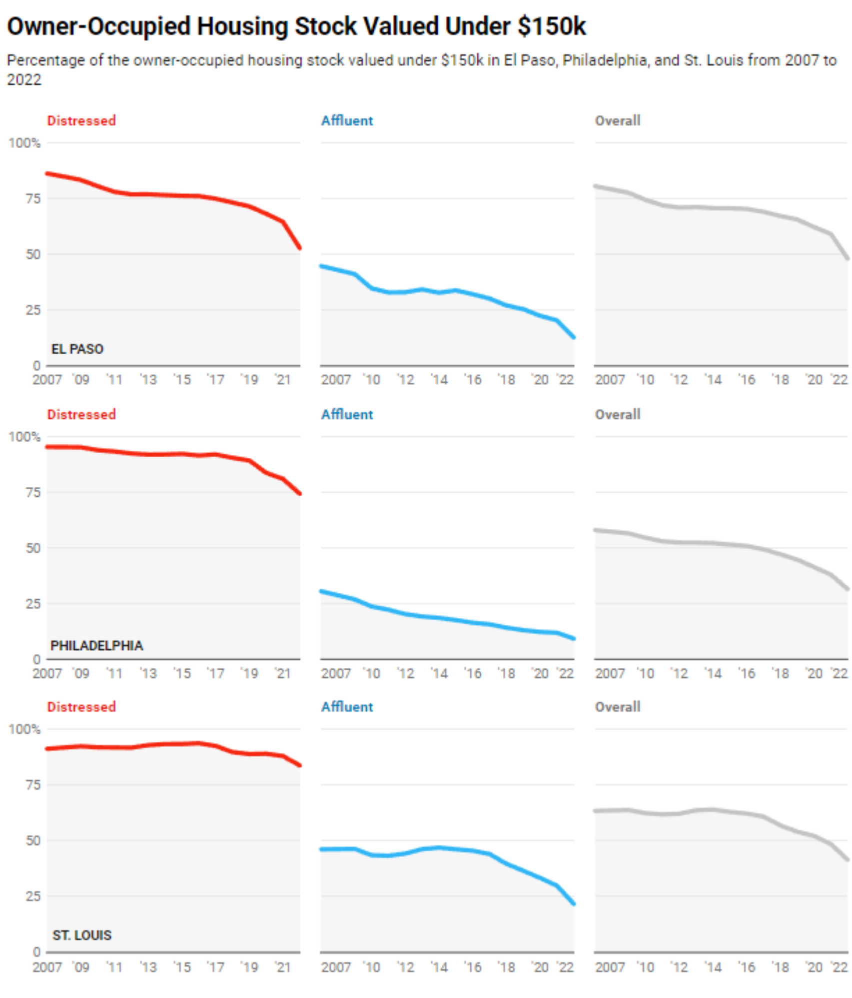


Chart: Craig J. Richardson Economic Consulting LLC • Source: American Community Survey (ACS) • Created with Datawrapper

https://datawrapper.dwcdn.net/Lfym4/2/

E. Housing in Distressed areas of all three cities is increasingly occupied by renters rather than owners, regardless of value.

Examining all occupied housing in Distressed areas regardless of assessed value, one can see that renters are taking an increasing share of housing stock from 2007 to 2022. Although El Paso's Distressed area has starkly higher levels of owner-occupied housing than the other two cities', with nearly 88 percent in 2007, the levels fell to 77 percent by 2022 as rental occupancy rates increased. In Philadelphia's Distressed area, owner-occupied housing was 55 percent in 2007, falling seven percentage points to 48 percent by 2022. Lastly, St. Louis' Distressed area had a nearly 50-50 split between renter and owner-occupied housing in 2007, but by 2022 renter-occupied housing made up 56 percent, with 44 percent left as owner-occupied housing. These changes can at least partially be explained by the dearth of access to small-dollar mortgage loans, as seen earlier.

Figure 15. Change in renter-occupied and owner-occupied housing share in El Paso

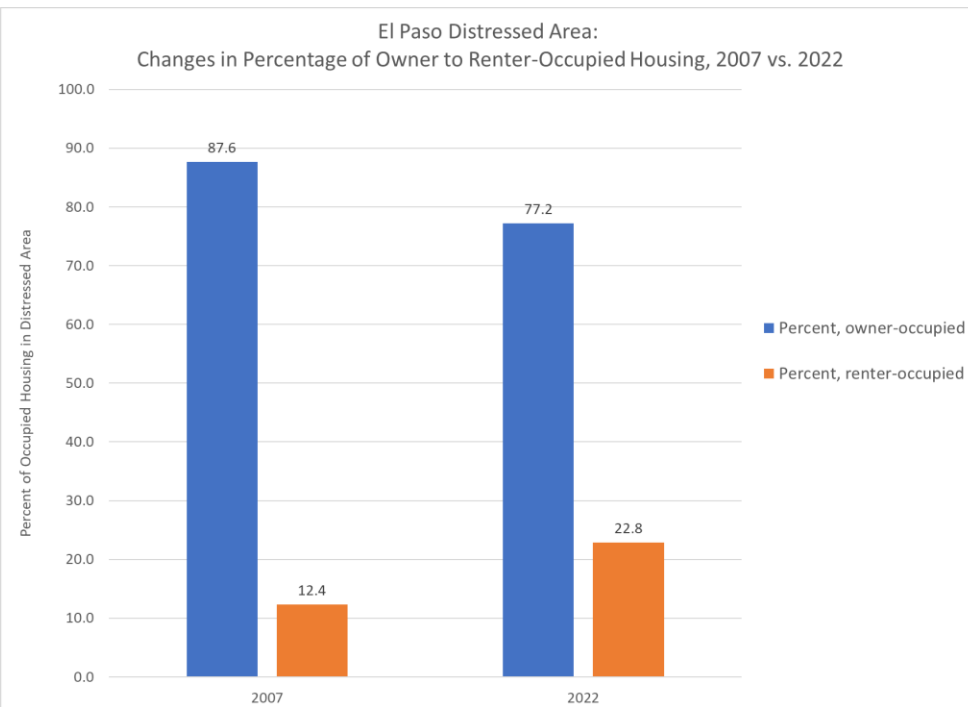


Figure 16. Change in renter-occupied and owner-occupied housing share in Philadelphia

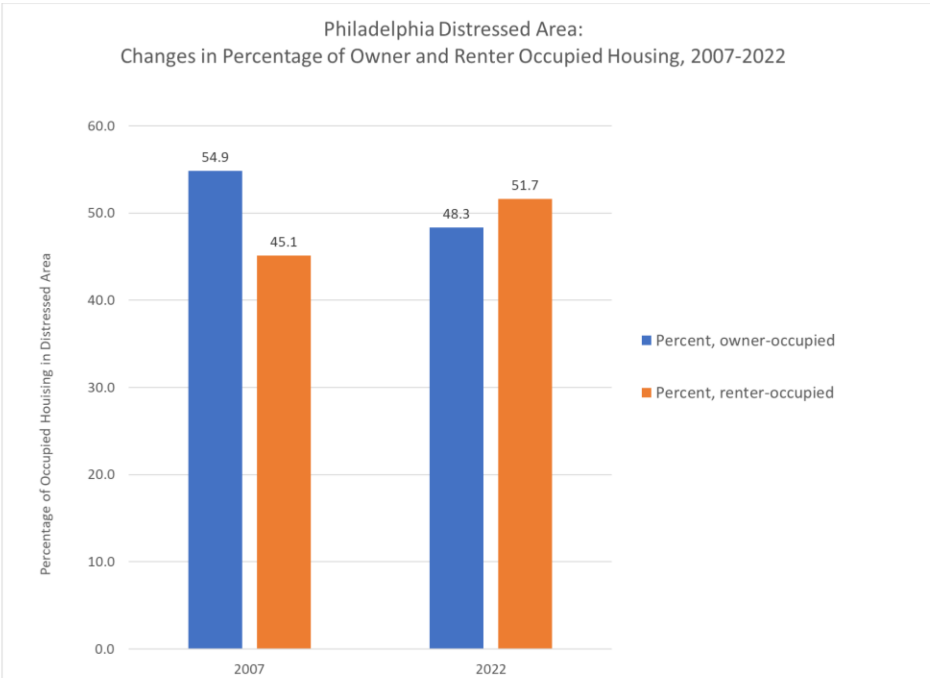
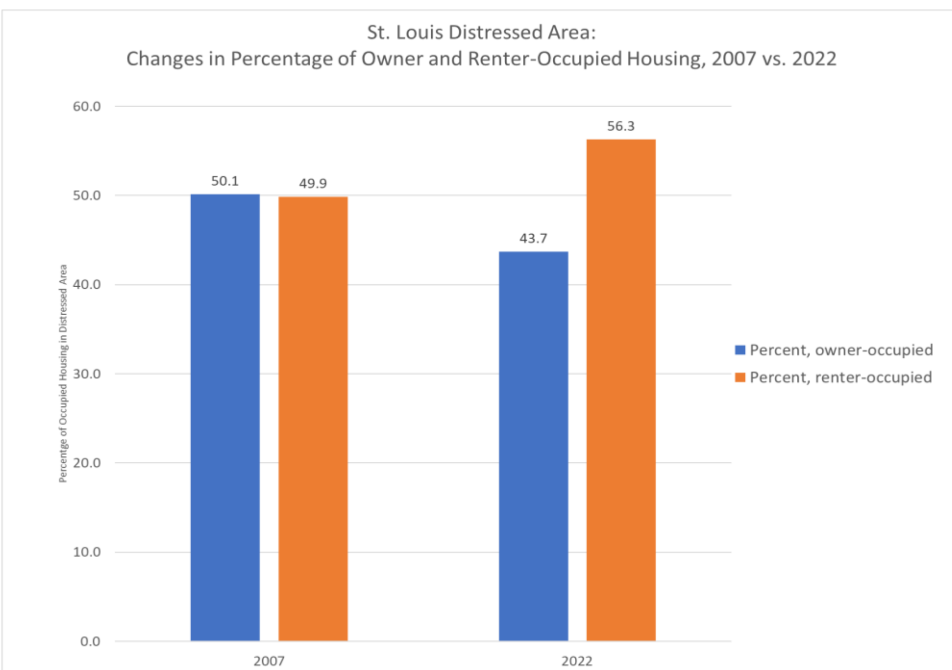


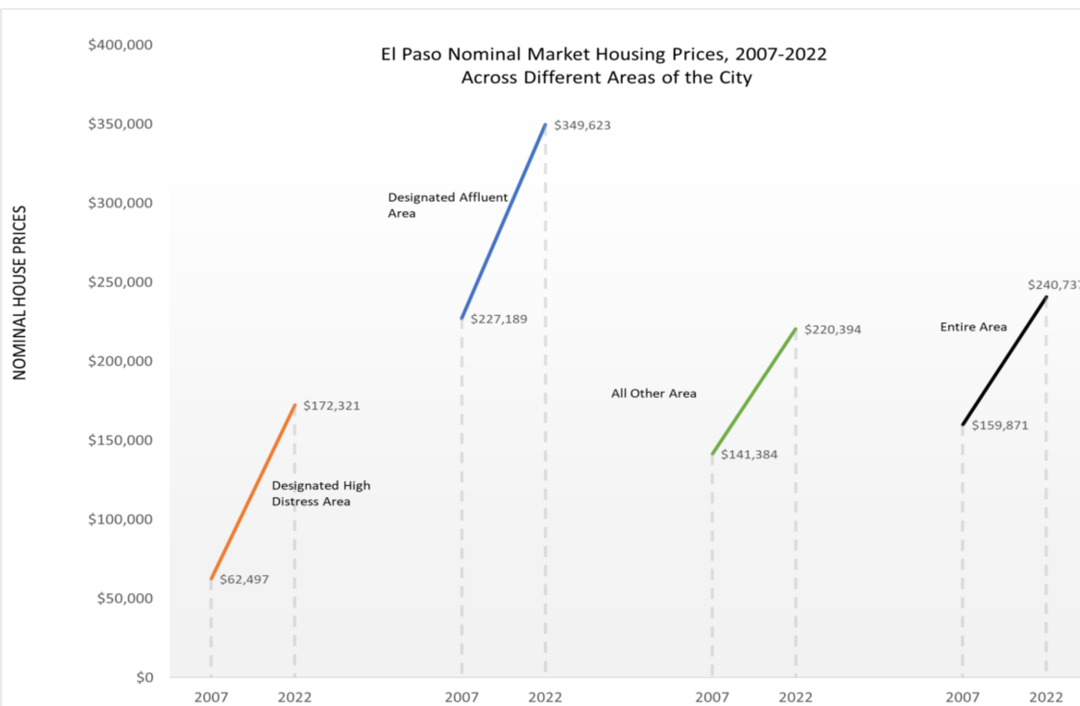
Figure 17. Change in renter-occupied and owner-occupied housing share in St. Louis



F. Nominal housing prices have been rising in nearly all areas between 2007 and 2022, but Distressed areas have had sharply different price trends depending on the city. Nominal housing prices in Affluent areas are more uniformly increasing.

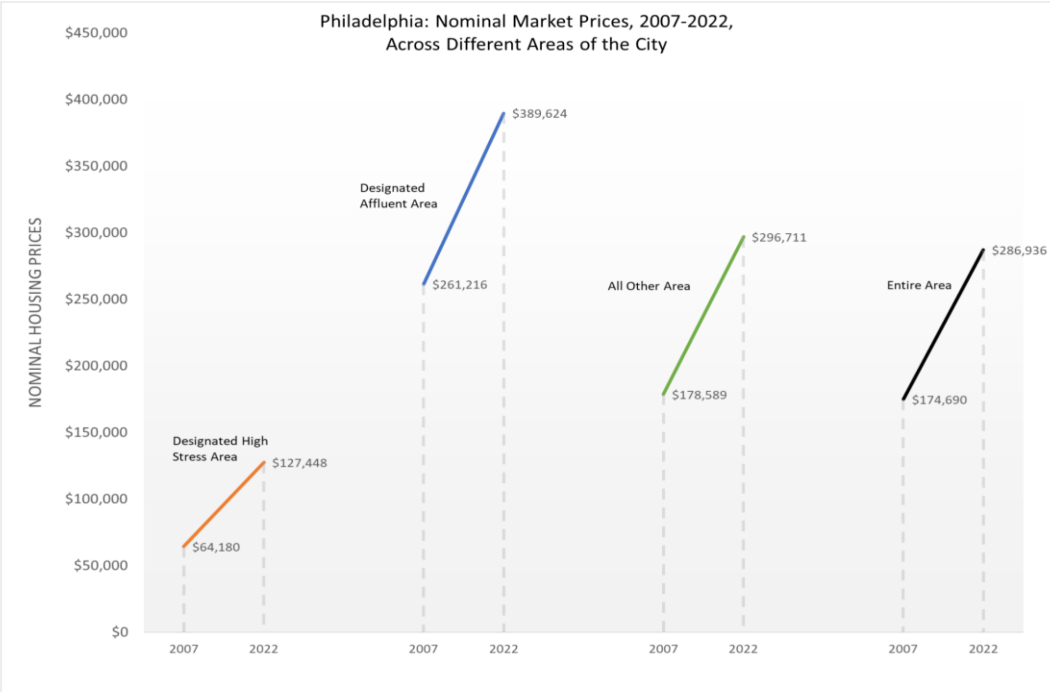
Nominal housing prices have been rising in nearly all areas between 2007 and 2022, but Distressed areas have had sharply different price trends, depending on the city. Nominal housing prices in Affluent areas are more uniformly increasing. Distressed areas have had sharply different rates of price changes between 2007 and 2022, depending on the city, ranging from -4 percent in St. Louis, 99 percent in Philadelphia and 175 percent in El Paso. On the other hand, nominal housing prices in Affluent areas across all three cities have risen at more consistent rates over the same time period, hovering between 33 and 35 percent, as seen in Table 2 below. Each change is likely due to local market conditions. These could be caused by differences in investment patterns, city planning, residuals of past structural racism in lending policies (i.e., redlining), and other factors. In addition, as home prices rise more quickly in Affluent areas, this inevitably leaves fewer properties priced at less than $150,000.

Figure 18. Change in nominal house prices in El Paso



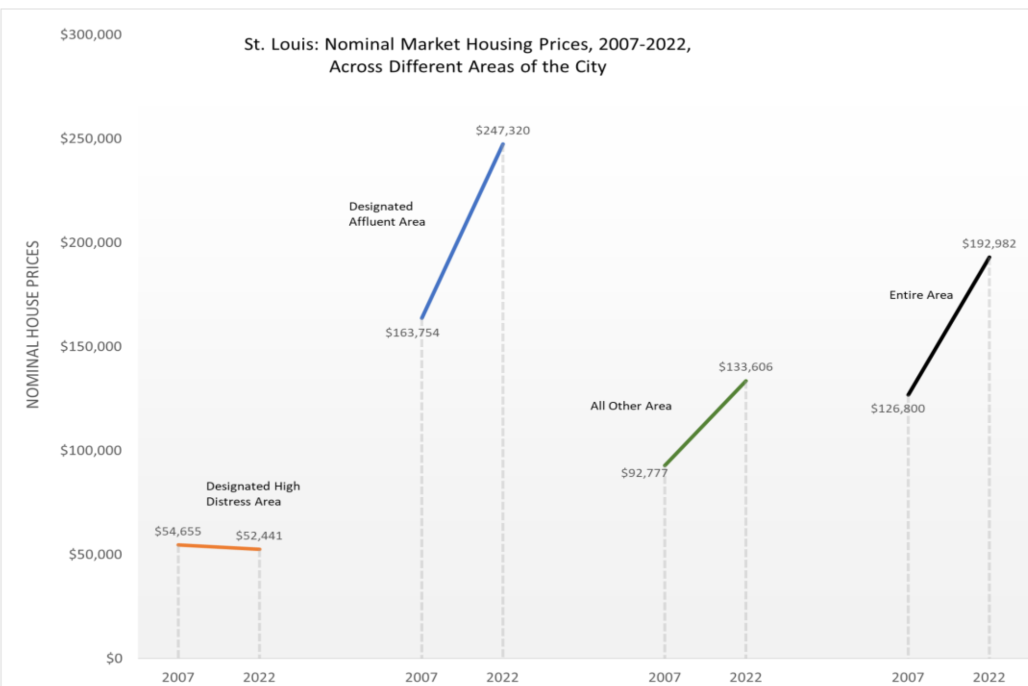
Note: Average nominal housing prices were estimated using CoreLogic data that comes from houses sold in that calendar year in that designated area.

Figure 19. Change in nominal house prices in Philadelphia



Note. Average nominal housing prices were estimated using CoreLogic data that comes from houses sold in that calendar year in that designated area.

Figure 20. Change in nominal house prices in St. Louis



Note. Average nominal housing prices were estimated using CoreLogic data that comes from houses sold in that calendar year in that designated area.

Table 2. Change in house prices in El Paso, Philadelphia, and St. Louis

Changes in Housing Prices: El Paso, Philadelphia, and St. Louis (2007-2022)

	Nominal Housing Prices, Percent Change (2007-2022)			Average Nominal Housing Prices, by Designated Area					
				High Distress		Affluent		All Other	
City	High Distress	Affluent	All Other	2007	2022	2007	2022	2007	2022
El Paso	175.7%	35.0%	55.9%	$62,497	$172,321	$227,189	$349,623	$141,384	$220,394
Philadelphia	98.6%	33.0%	66.1%	$64,180	$127,448	$261,216	$389,624	$178,589	$296,711
St. Louis	-4.1%	33.8%	44.0%	$54,655	$52,441	$163,754	$247,320	$92,777	$133,606

Note: Average nominal housing prices were estimated using CoreLogic data that comes from houses that were sold in that calendar year in that designated area.

G. Between 2007 and 2022, Philadelphia's and El Paso's Distressed communities saw a rapid rise in housing unaffordability as income gains lagged behind housing price growth. For those cities' Affluent areas, on the other hand, housing affordability has increased. St. Louis had greater affordability across all areas over the same time span.

To track housing affordability, we created an index that captures the simultaneous effect of changing house prices and changing incomes over time, in the area that people live, similar to Harvard University's Joint Center for Housing Studies' Home Price to Income Ratio method. This gives a sense of purchasing power of buying a house in one's neighborhood, working at prevailing incomes in the same neighborhood.

We do that by taking the average price of homes for sale in a given area using CoreLogic data (Distressed or Affluent) and dividing it by the per capita income in the same area using ACS data. This indicates trends in whether one needs to work a longer or shorter time to buy a house, given the prevailing wages in the designated areas of the city.

Housing Affordability Index for Distressed or Affluent area in year i,

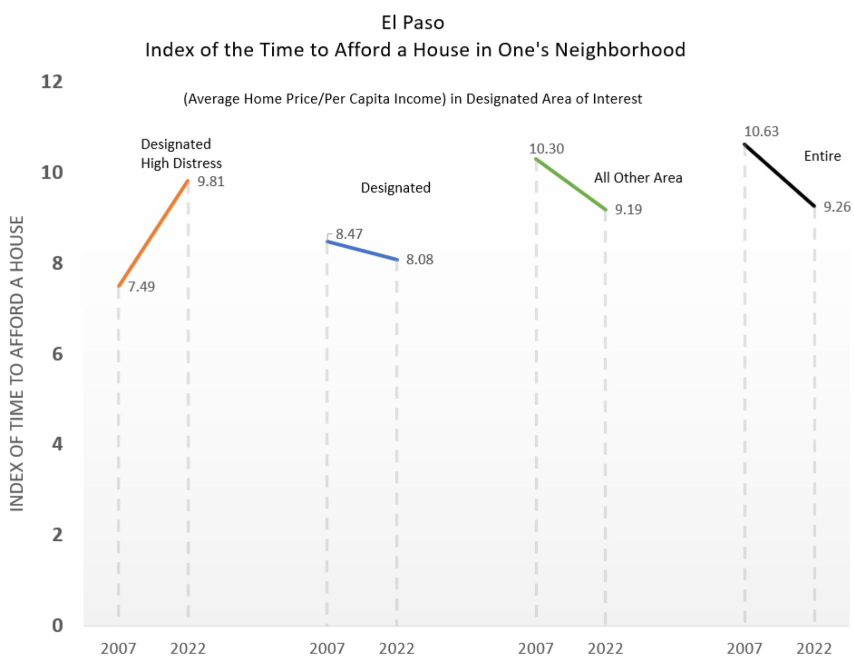
$$= \frac{\text{Average selling price of homes}}{\text{Per capita income}}$$

A higher index number usually indicates that the home prices are rising faster than per capita incomes in the respective area of interest, making these homes more unaffordable for the residents in that area. For both Philadelphia and El Paso, only Distressed areas are seeing a rise in the index, meaning that homes are becoming more unaffordable for those living in the lowest-income areas of the city. The Affluent and All Other areas are seeing per capita incomes rise faster than median home prices, making these areas more affordable from 2007 to 2022 for those who reside in the respective areas.

St. Louis is the only city seeing increasing housing affordability across the board in terms of purchasing power of residents, since wages rose much faster than housing prices. However, despite Distressed areas of St. Louis having rising housing affordability, this is caused by falling nominal housing prices, a potential sign of a stagnating local economy. This makes homes even more affordable but may be indicative of serious challenges in these areas. The underlying reasons for falling home prices can generally come from a fall in demand and/or a rise in supply of housing. In the case of St. Louis, declining home prices will mean that existing homeowners in Distressed areas are seeing a steady erosion of their wealth, exacerbating existing wealth gaps. It may also mean these homeowners are trapped in their homes, unable to sell because the value of the home is less than what they owe the bank. This can accelerate existing trends toward the concentration of poverty in Distressed areas. Thus, housing affordability should not be seen as an unalloyed positive phenomenon in every instance.

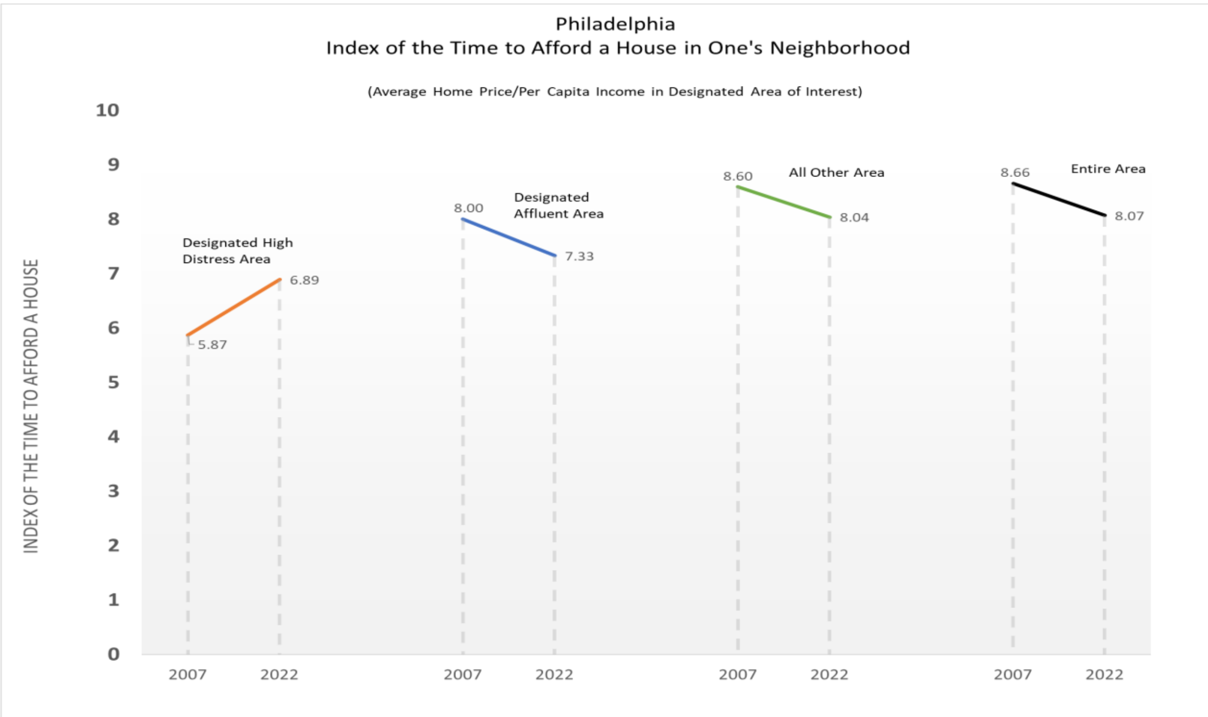
In sum, in cities where incomes rise at a faster rate than housing prices, this is indicative of a healthy and thriving economy that allows for a simultaneous building of household wealth and retains accessibility to the housing market.

Figure 21. Housing affordability index in El Paso



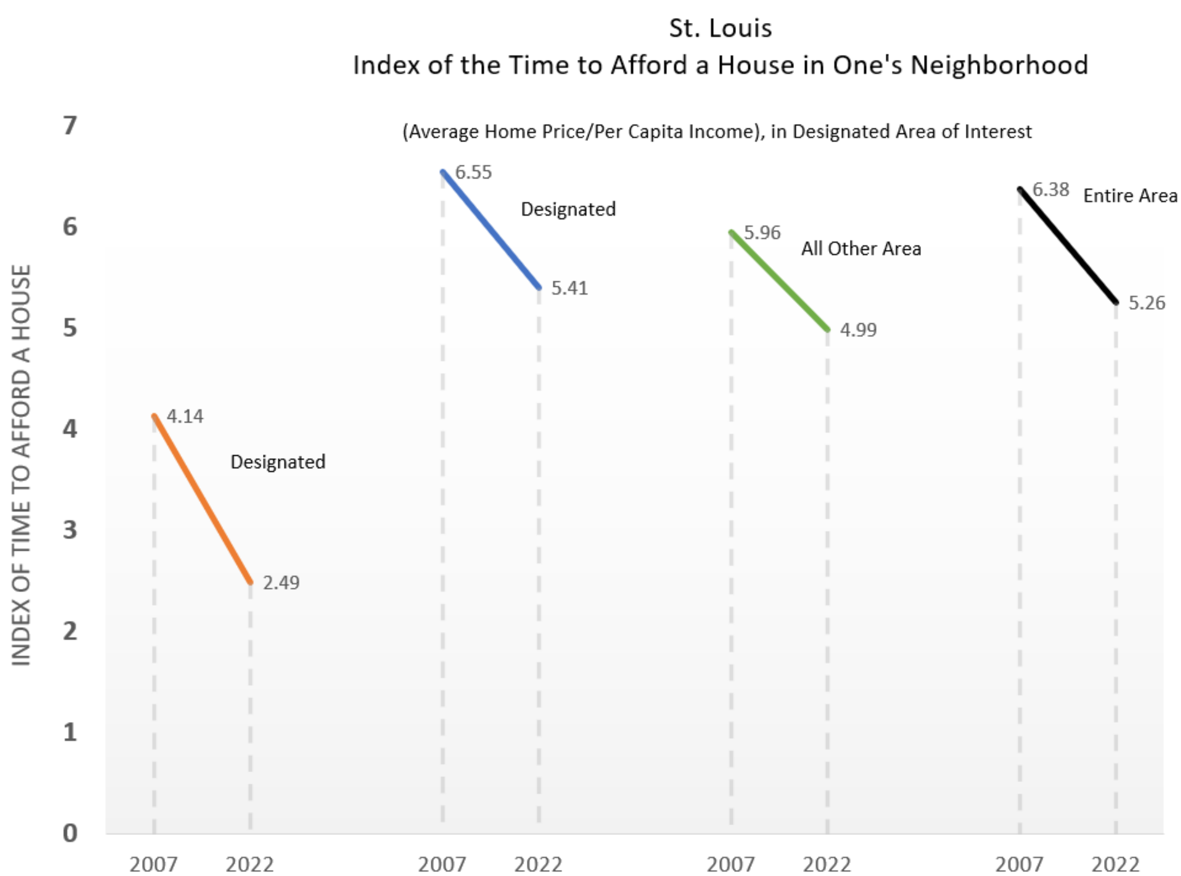
Note: Average nominal housing prices were estimated using CoreLogic data that comes from houses sold in that calendar year in that designated area, while income per capita comes from the ACS five-year estimates.

Figure 22. Housing affordability index in Philadelphia



Note: Average nominal housing prices were estimated using CoreLogic data that comes from houses sold in that calendar year in that designated area, while income per capita comes from the ACS five-year estimates.

Figure 23. Housing affordability index in St. Louis



Note: Average nominal housing prices were estimated using CoreLogic data that comes from houses sold in that calendar year in that designated area, while income per capita comes from the ACS five-year estimates.

H. Commute times to work are far higher for residents of Distressed communities vs. Affluent communities for all three cities.

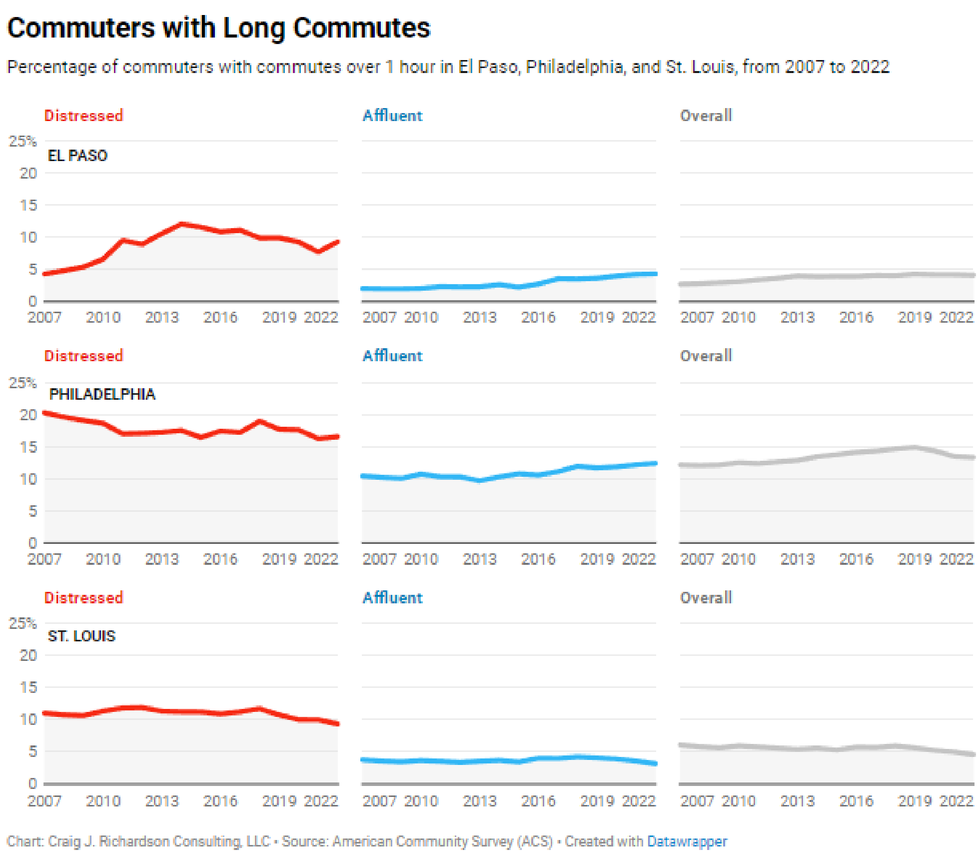
The link between easy access to work and housing affordability is not always made explicit. However, if lower income individuals are commuting long hours by bus, and taking only jobs that exist along bus routes, their opportunities to save and invest will be sharply lower than if they could easily walk or ride a bicycle to work, as noted by Richardson (2019).

For those in Distressed communities, long commutes of over one hour occur for around 10 percent of El Paso residents, 17 percent for Philadelphia residents and 10 percent for St. Louis residents. This will exacerbate long-term trends in widening gaps between the poor, the middle-class, and the wealthy, since a vehicle becomes the necessary (and relatively expensive) key to access the economic network. Commute times are on a slight downward trend in distressed communities, perhaps reflecting improved public transit or wider roads.

As aptly noted in a 2019 Pew Charitable Trusts report on Philadelphia's public transportation network:

"Low-paying jobs, however, are dispersed throughout the city and the region. As a result, many low-income riders must make one or more transfers to get to work, incurring additional charges if the fare is paid in cash or with funds preloaded on smart cards, or they must make more expensive trips on Philadelphia's commuter rail system, known as Regional Rail. The areas in Philadelphia where costlier trips hit the hardest are those where incomes are low, many households do not have cars, and using SEPTA to get to work requires one or more transfers."

Figure 24. Commuters with commutes over one hour



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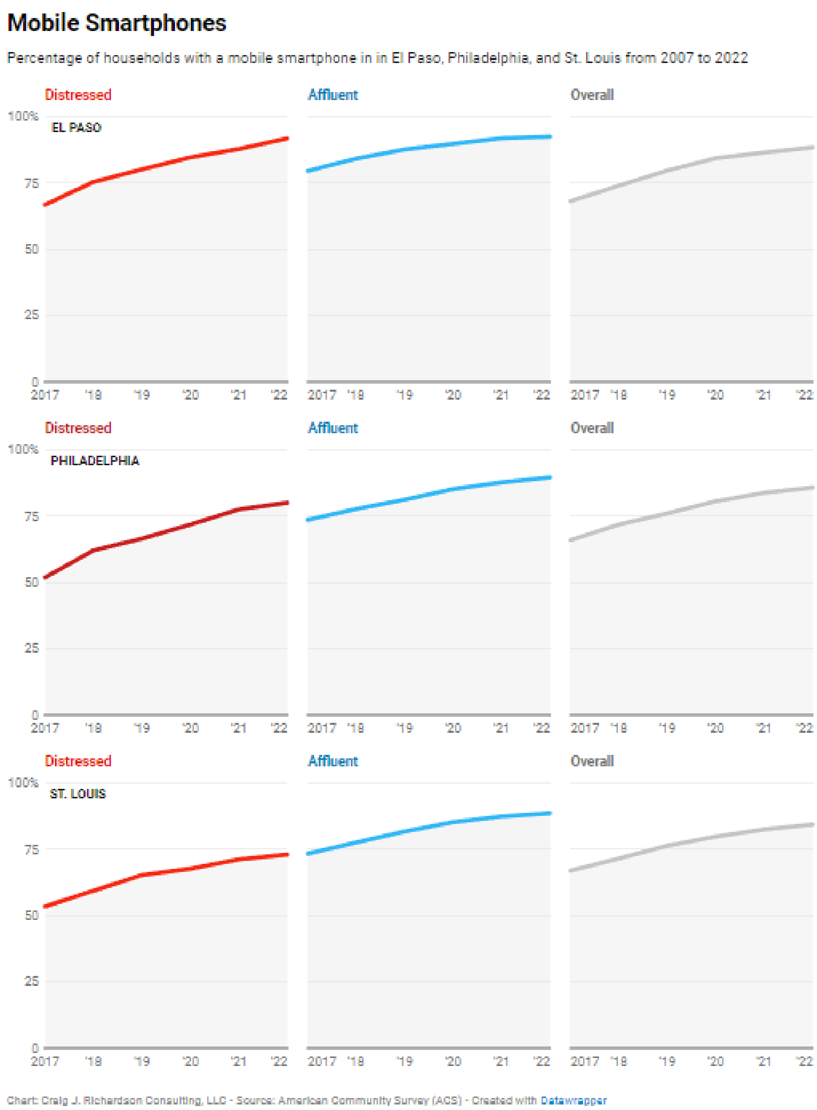
I. Social trends: Since 2017, technology access has sharply improved for residents of distressed communities. These trends may be because of falling smartphone prices, greater access to free wireless networks, and eligibility for inexpensive Android phones through the Lifeline Program, which also subsidizes broadband internet access.

This can only improve access to better housing even in tight housing markets for low-income earners. Better technology and internet access means better access to knowledge of mortgage lenders and competitive interest rates, affordable housing options in designated neighborhoods, and government agencies that offer financial literacy classes around home affordability.

Figure 25. Share of households with a smartphone



Educational attainment is improving for more residents of Distressed communities. The percentage of the population age 25 and up that has less than a high school education is decreasing, with the largest decreases in Distressed areas of all three cities.

On the other hand, a small fraction of residents aged 25 and up in Distressed areas get more than a four-year degree, in contrast to rising numbers in Affluent areas since 2007. Higher educational attainment can lead to higher incomes, enabling individuals and families to better keep up with rising home prices.

Figure 26.

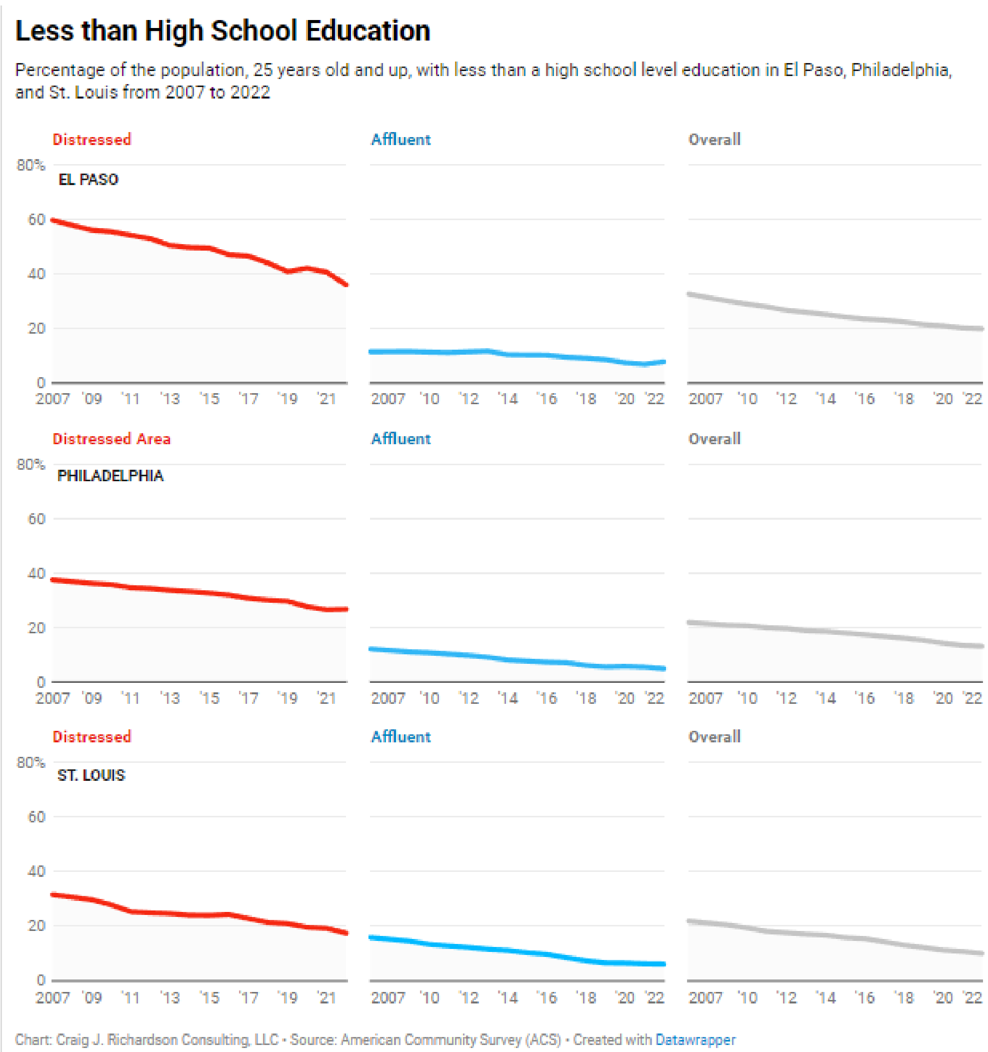


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Figure 27. Adult population with more than a four-year degree

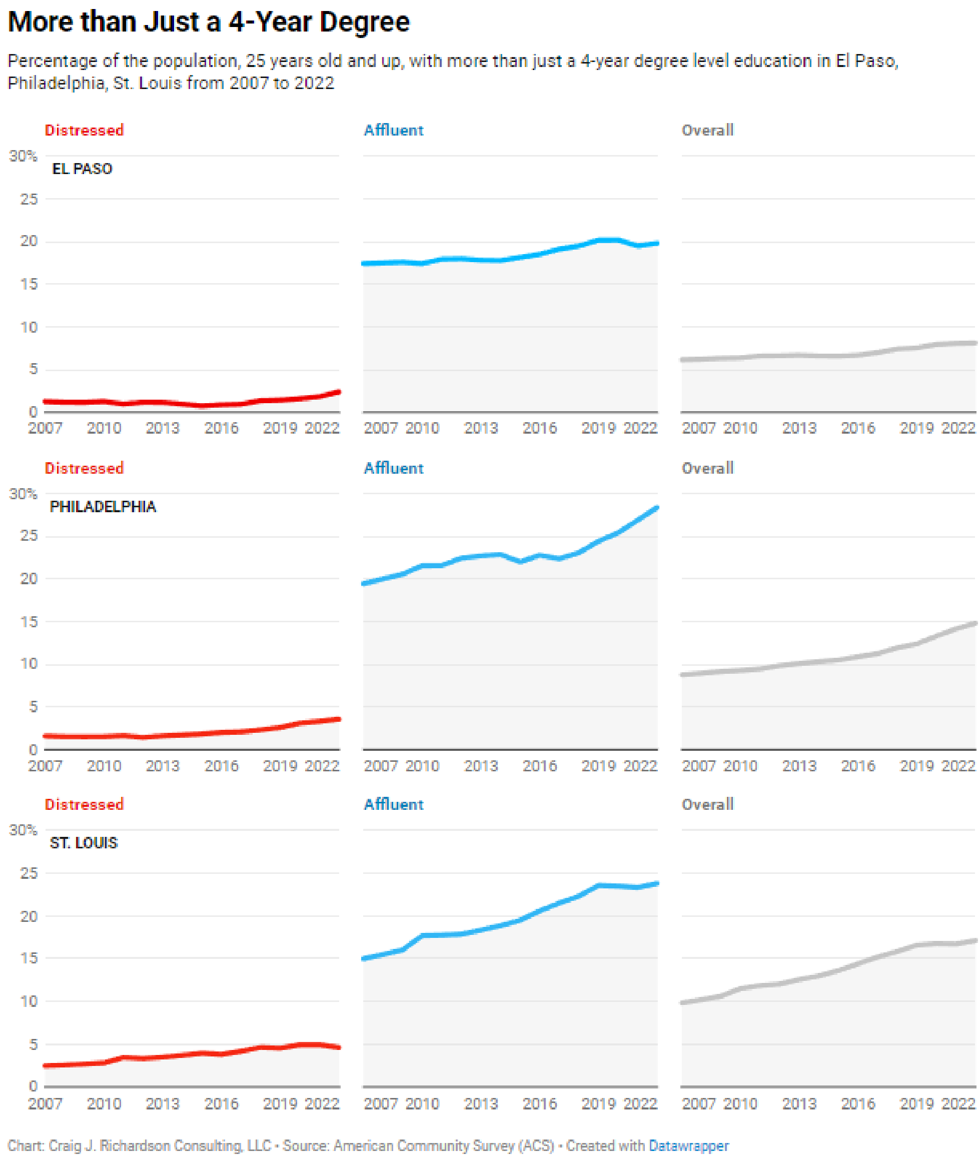

Chart: Craig J. Richardson Economic Consulting LLC • Source: American Community Survey (ACS) • Created with Datawrapper

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IV. Conclusion

A. Summary of findings

Despite rising home prices, there were still plenty of owner-occupied homes assessed at $150,000 or less in Philadelphia, St. Louis, and El Paso in 2022. This was particularly true in Distressed areas of those cities.[4]

Thus, the severe drop in small-dollar mortgage applications and originations after 2008 cannot be explained solely by a decline in the stock of small-dollar housing valued at $150,000 or less. More likely, the Great Recession and the more onerous banking regulations instituted by the 2010 Dodd-Frank Act made these smaller mortgages unprofitable for most lenders. In addition, for large institutions who can spread those costs out over more loans, their business decisions about paying large sums for top brokers also makes those loans unprofitable. Even if they could charge what they wanted in points and fees, it still doesn't make it worth the time relative to larger loans.

Since then, all-cash buyers have entered into Distressed areas, buying up a greater proportion of small-dollar homes.

In all three cities, there was a slow but steady rise in the percentage of renter-occupied housing in Distressed areas from 2007 to 2022. The share of households that rent in El Paso's rose more than 10 percentage points, from 12.4 percent to 22.8 percent. Philadelphia's renter share rose from 45.1 percent to 51.7 percent, a 6.6 percentage point change. Lastly, St. Louis saw its rental share move from 49.9 percent to 56.3 percent over the same time period. In the cities' Affluent areas, there was a similarly slow but steady increases in the rates of renter-occupied housing over the same time period.

Nominal house prices rose in nearly all areas of the three cities between 2007 and 2022. But price growth varied in Distressed areas depending on the city, ranging from -4 percent in St. Louis to 175 percent in El Paso. Meanwhile, nominal housing prices in Affluent areas rose at more consistent rates over the same time period, hovering between 33 and 35 percent over the study period.

With both nominal house prices and nominal incomes on the rise, using an index of housing affordability provides a clearer measure of housing access than adjusting for inflation. We use the average house selling price in a given year divided by per capita income, defined for each city and neighborhood area. Philadelphia's and El Paso's Distressed communities are seeing a rapid rise in housing unaffordability as income

[4] Note that for these properties, the values come from the American Community Survey and are owner-assessed, and thus represent a subjective value that is highly correlated with market values or commercial assessors' but may deviate from those values.

gains lag behind housing price growth. This is in contrast to St. Louis, which has had wage growth in excess of house price growth, leading to greater affordability. However, nominal housing prices in St. Louis' Distressed area are falling, a possible indication of an area that is experiencing economic decline. In the case of falling nominal housing prices, this type of "rising affordability" must be balanced with the knowledge that household wealth is falling for existing homeowners. In contrast, Affluent areas of Philadelphia and El Paso are becoming more affordable, as income gains outpace the price of housing in these areas.

There are other factors at work that potentially affect housing access for those living in Distressed communities. For example, commute times to work are far higher for residents of Distressed communities compared to Affluent communities for all three cities, making it more difficult to earn the income necessary to afford a home purchase. On the positive side, since 2017, technology access has sharply improved for residents of Distressed communities, which can serve as an information tool to better leverage opportunities in the housing market. Lastly, educational attainment is improving for more residents of Distressed communities that will help link them to better jobs and potentially higher incomes.

B. Policy implications, limitations, and future research

Research into El Paso, St. Louis, and Philadelphia provides evidence that access to housing is becoming less accessible and less affordable for many residents. In separately analyzing Distressed and Affluent areas, our report finds that Distressed areas are the most fragile when put under external stress from economic downturns. This means that public policies around housing and banking legislation should be similarly tailored to individual cities, community institutions, and neighborhood areas if possible. Otherwise, national housing policies create unintended consequences if they are formulated on a one-size-fits-all perspective.

Although this study reports trends rather testing a formal causative economic model, there is evidence of a correlation between post-Great Recession banking policies meant to shore up the U.S. banking system and the collapse of small-dollar lending in two of the three cities studied (the third, El Paso, has had an ongoing high level of owner-occupied housing, making it a very different case study from St. Louis and Philadelphia).

Since 2007, the increase in investor-owned rental housing within these three cities may be seen by some as a pernicious outcome of a market that needs further legislation to “correct.” However, policymakers may exacerbate the challenges of housing access if they do not understand some of the roots of the problem.

We suggest that federal policies should take into account the history of community and local government involvement in lending markets and be careful about imposing new oversight burdens that may be shouldered more easily by larger, better-capitalized Wall Street banks. Notably, from 2007 through 2013, the number of independent commercial banks shrank by 14 percent, or more than 800 institutions, with the majority of losses coming from community bank closures. Smaller lenders in communities better know their customers’ needs and potential for repaying loans, beyond just relying on simple metrics like credit scores.

In the past, trust between the local lenders and their customers created greater access to small-dollar mortgages, particularly in Distressed communities that we have studied. These smaller lenders that kept the mortgages in-house directly bore the costs or benefits of their lending practices and were incentivized to closely study the risk of each loan. They knew their customers by name and these social relationships provided reasons for both parties to do right by each other. Trust between the two parties lowered costs by lessening the need for outside audits and compliance.

Rather than building trust with personal relationships, the largest banks took a different route by turning mortgages into impersonal commodities that could be sold quickly and efficiently. These practices became widespread by the early 2000s in the runup to the Great Recession. In order to increase profits, these banks packaged high-risk subprime mortgages into opaque securities that hid the true nature of the loans’ credit worthiness. Trust in these complex financial instruments was artificially manufactured, with Wall Street banks shopping for the credit agency that gave the highest rating for these risky mortgage securities. These securities were often sold to other unsuspecting institutions, thus infecting the financial system with subprime mortgages lurking under the guise of AAA-rated securities. When hundreds of thousands of these subprime mortgages failed, taking with it hundreds of banks, the 2010 Dodd-Frank banking legislation aimed to prevent another large scale financial crash, with more than 400 new banking regulations.

In large part, the nation’s smaller lenders have been penalized for how the larger banks broke trust in the banking system and they have had to shoulder higher overhead costs as a result. Rebuilding trust, by recognizing *how* banks do business should be a way to review how banking regulations are imposed upon smaller banks that serve local customers. Banks that hold onto customers’ mortgages, invest in social capital and develop community relationships may lower their short-term profits, but the mutual trust that is developed provides greater stability for the banking system in the long run.

Other local public policies should seek ways to link residential, shopping, and business districts that do not require long driving distances or time-consuming commutes on public transportation. When labor productivity increases, so do wages and incomes, allowing homes to become more affordable. In this way, millions more Americans will gain hope to access the American Dream through acquiring a house of their own.

The report's central strength—a deep dive into three U.S. cities—is also its limitation, since it is difficult to draw conclusions around national policies from three cities alone. Future research could broaden this methodological approach to more cities to find out if the trends carry across regions of the Western and New England areas of the United States. In addition, the combined ACS, HMDA, and CoreLogic dataset that has been produced as part of this report would be well suited to employing regression analysis. This type of analysis could investigate changes in access to small-dollar mortgages as a function of a number of important independent variables to help researchers identify the most important changes needed to improve mortgage access for U.S. families on the lower end of the economic ladder.

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Appendix A: Creating the Dataset

Here we provide additional details regarding the methods and data used for the project. We begin by documenting the methods related to the project's unit of analysis. Then we discuss the various data sources and the steps taken to process data collected from these sources. Many tables are provided to organize the material and improve the explanations.

A. Standardizing the Unit of Observation

From the outset of this project, our goal was to analyze changes across neighborhoods in three cities in the United States (El Paso, Philadelphia, and St. Louis) with as wide of a time-related lens as data permitted. Regarding the datasets used (Home Mortgage Disclosure Act, CoreLogic, and American Community Survey), which we discuss further below, the widest overlapping range of years is 2007-2022. To proxy for neighborhoods, we rely on census tracts, which are a commonly used proxy for neighborhoods (Cox, Henwood, Rodnyansky, Rice, and Wenzel, 2019; Horowitz, 2019; Chan, Gedal, Been, and Haughwout, 2013).

One particular challenge with census tracts is that every 10 years, the U.S. Census Bureau updates census tract boundaries (i.e., the geographic polygonal shape that defines a census tract). In most cases, census tract boundaries do not change. However, in some cases census tracts are either 1) combined into larger tracts, 2) split into smaller tracts, or 3) completely redefined. These cases make it challenging to measure changes in census tracts over time frames that include instances when boundaries are redefined. To address these issues, census tracts must be standardized over time, so that apples-to-apples comparisons can occur. Researchers will often use a variety of different kinds of areal interpolation to "standardize" census tracts, which is a method that essentially weights census counts by the proportion of a tract that falls into a newly designed tract. These methods have serious weaknesses, with one being that the weighting process inherently assumes that people, households, or housing units are evenly distributed across the census tract's land space (Logan, Zhang, Stults, and Gardner, 2021). To further complicate matters, ACS data are estimates with variance, so using areal interpolation techniques on numbers that are already estimates can be problematic (Logan et al., 2021).

Therefore, we decided to take a different approach to standardize census tracts, which was reviewed and approved by the Pew team. The method involved manually assembling new census tract boundaries. We refer to these as "reconstructed census tracts." These reconstructed census tracts were created by visually examining census tract boundary definitions in 2000, 2010, and 2020 and piecing them back together in cases when tracts split apart or changed, so that the outer boundaries of the new reconstructed tract were stable over time. In the few cases when tracts were completely redrawn, the surrounding tracts, including the one that was redrawn, were combined so that the outer boundaries were consistent across each of the boundary changes. This method was extremely time-intensive, but we were able to complete it because we only had to work with three cities. We believe this method, though burdensome to implement, is extremely advantageous in that it does not involve making additional assumptions about how counts ought to be spread across a land space.

We created a unique key that we assigned to our reconstructed census tracts, which established the relationship between the relevant census tracts across time, so that we could reaggregate our data to the new keys. Then, we calculated our relevant statistics at the reconstructed census tract level.

B. Implementing the new key for the reconstructed census tracts for the three Cities

For the years 2000-2009, census tract boundaries followed the boundary definitions established in the 2000 decennial census. For the years 2010-2019, census tract boundaries follow the boundary definitions established in the 2010 decennial census. For the years 2020-2029, census tract boundaries follow (will follow) the boundary definitions established in the 2020 decennial census. This is further summarized in Table A1 below.

Table A1. Census Boundaries and Their Years

Years	Census Boundaries
2000 - 2009	2000
2010 - 2019	2010
2020 - 2029*	2020

At the writing of this report, census-related data is only available up to year 2022

Table A2 summarizes how the number of distinct tracts changed in our three study areas, as boundary definitions changed with subsequent decennial censuses. The number of distinct tracts in El Paso and Philadelphia increased from one decennial census to the next, even though the county boundaries did not change, meaning that census tracts were further divided into smaller tracts. St. Louis is different, however. The number of distinct tracts *declined* from one census to the next, meaning that some tracts were combined with other tracts to form a larger tract. Along with the changes in the total distinct tracts, there were some tracts that had their boundaries redrawn. To determine this, we manually examined boundary maps.

Table A2. Distinct Tracts in the Three Jurisdictions

County	Year	Boundary Definition Year	Number of Distinct Census Tracts
El Paso County	2000 - 2009	2000	126
El Paso County	2010 - 2019	2010	161
El Paso County	2020 - 2029*	2020	181
Philadelphia	2000 - 2009	2000	381
Philadelphia	2010 - 2019	2010	384
Philadelphia	2020 - 2029*	2020	408
St. Louis	2000 - 2009	2000	113
St. Louis	2010 - 2019	2010	106
St. Louis	2020 - 2029*	2020	104

The next three tables summarize how we established the reconstructed census tracts using our key. The first table (Table A3) describes the steps taken for El Paso, the second (Table A4) describes the steps taken for Philadelphia, and the third table (Table A5) describes the steps taken for St. Louis. The tables list the specific tracts that changed and the resulting reconstructed tract that was formed.

Table A3. El Paso

Change	For the 2000 Boundaries	For the 2010 Boundaries	For the 2020 Boundaries	Outcome
1	Combine tracts 001201 and 001203	Combine tracts 001201 and 001203	Leave tract 001204 alone	The boundaries for the specified tracts for 2000 and 2010 are set to equal the tract definition for 001204 in 2020
2	Combine tracts 000500 and 000700	Leave tract 010600 alone	Combine tracts 010601 and 010602	The boundaries for the specified tracts 2000 and 2020 are set to equal the tract definition for 010600 in 2010

3	Combine tracts 010318 and 010101	Combine tracts 010319, 010340, 010339, and 010101	Combine tracts 010364, 010358, 010359, and 010101	The resulting combination creates a new boundary

Table A4. Philadelphia

Change	For the 2000 Boundaries	For the 2010 Boundaries	For the 2020 Boundaries	Outcome
1	Leave tract 005000 alone	Leave tract 005000 alone	Rename tract 989200 to 005000	Tract 989200 in the 2020 boundaries is the same as tract 005000 in the 2000 and 2010 boundaries
2	Combine tracts 004600, 005200, 002600, 004300, 004900, 004800, 004700, 005100, 003800, 005800, 005700, 006800, 006900, 003500, 003400, 007500, and 005900	Combine tracts 980900, 980400, 003800, 037300, 980600, 980700, 003300, and 006900	Combine tracts 980905, 980901, 980400, 980906, 980904, 980903, 980902, 039100, 003300, 037300, 980600, 980701, and 980702	There's a large chunk of space in Philadelphia that does not neatly assemble or disassemble into a clear subset of census tracts. These census tracts need to be joined together to ensure an apples-to-apples comparison of land space between the 2000, 2010, and 2020 boundaries
3	Combine tracts 004400 and 004500	Leave tract 037200 alone	Leave tract 037200 alone	The boundaries for the specified tracts in 2000 are set to equal the tract

				definition for 037200 in 2010 and 2020
4	Combine tracts 007600 and 008900	Leave 036900 alone	Combine tracts 036901 and 036902	The boundaries for the specified tracts in 2000 and 2020 are set to equal the tract definition for 036900 in 2010
5	Combine tracts 009700, 009800, 011600, and 009900	Combine tracts 980800, 037500, 009802, and 009801	Combine tracts 980800, 037500, 009802, and 009801	The resulting combination creates a new boundary
6	Combine tracts 012300, 015000, and 012400	Leave tract 980000 alone	Combine tracts 980001, 980003, and 980002	The boundaries for the specified tracts in 2000 and 2020 are set to equal the tract definition for 980000 in 2010
7	Combine tracts 012600 and 012700	Leave tract 037600 alone	Leave tract 037600 alone	The boundaries for the specified tracts in 2000 are set to equal the tract definition for 037600 in 2010 and 2020
8	Combine tracts 013000, 012800, and 012900	Leave 036700 alone	Leave 036700 alone	The boundaries for the specified tracts in 2000 are set to equal the tract definition for 036700 in 2010 and 2020
9	Combine tracts 015400 and 015500	Leave 037700 alone	Leave 037700 alone	The boundaries for the specified tracts in 2000 are set to equal the tract definition for 037700 in 2010 and 2020
10	Combine tracts 015900, 018100, and 018200	Leave 037800 alone	Leave 037800 alone	The boundaries for the specified tracts in 2000 are set to equal the tract definition for 037800 in 2010 and 2020

11	Combine tracts 018600 and 018500	Leave 037900 alone	Leave 037900 alone	The boundaries for the specified tracts in 2000 are set to equal the tract definition for 037900 in 2010 and 2020
12	Combine tracts 018700 and 018900	Leave 038200 alone	Leave 038200 alone	The boundaries for the specified tracts in 2000 are set to equal the tract definition for 038200 in 2010 and 2020
13	Combine tracts 019300, 019600, and 019400	Leave 038300 alone	Combine 989300 and 038301	The boundaries for the specified tracts in 2000 and 2020 are set to equal the tract definition for 038300 in 2010
14	Leave 019700 alone	Combine tracts 019700 and 980500	Combine tracts 019700 and 980500	The boundaries for the specified tracts in 2010 and 2020 are set to equal the tract definition for 019700 in 2000
15	Combine tracts 022100 and 022200	Leave 038400 alone	Leave 038400 alone	The boundaries for the specified tracts in 2000 are set to equal the tract definition for 038400 in 2010 and 2020
16	Rename tract 022300 to 980100	Leave 980100 alone	Leave 980100 alone	Rename a tract in 2000
17	Combine tracts 022400 and 022800	Leave 038500 alone	Leave 038500 alone	The boundaries for the specified tracts in 2000 are set to equal the tract definition for 038500 in 2010 and 2020
18	Combine tracts 022500, 022600, and 022700	Leave 038700 alone	Leave 038700 alone	The boundaries for the specified tracts in 2000 are set to equal the tract definition for 038700 in 2010 and 2020

19	Combine tracts 022900, 023000, and 023400	Leave 038600 alone	Leave 038600 alone	The boundaries for the specified tracts in 2000 are set to equal the tract definition for 038600 in 2010 and 2020
20	Combine tracts 025100 and 025000	Leave 038900 alone	Leave 038900 alone	The boundaries for the specified tracts in 2000 are set to equal the tract definition for 038900 in 2010 and 2020
21	Combine tracts 029500 and 029600	Leave 038000 alone	Leave 038000 alone	The boundaries for the specified tracts in 2000 are set to equal the tract definition for 038000 in 2010 and 2020
22	Combine tracts 029700, 032200, 032400, and 032700	Leave 038100 alone	Leave 038100 alone	The boundaries for the specified tracts in 2000 are set to equal the tract definition for 038100 in 2010 and 2020
22	Combine tracts 030400 and 030300	Leave 039000 alone	Combine tracts 039001 and 039002	The boundaries for the specified tracts in 2000 and 2020 are set to equal the tract definition for 039000 in 2010
23	Rename 032800 to 989100	Leave 989100 alone	Leave 989100 alone	Rename a tract in 2000
24	Rename 034300 to 980200	Leave 980200 alone	Leave 980200 alone	Rename a tract in 2000
25	Rename 035400 to 980399	Leave 980300 alone	Leave 980300 alone	Rename a tract in 2000
26	Combine 023200 and 023300	Leave 038800 alone	Leave 038800 alone	The boundaries for the specified tracts in 2000 is set to equal the tract definition for 038800 in 2010 and 2020

Table A5. St. Louis

Change	For the 2000 Boundaries	For the 2010 Boundaries	For the 2020 Boundaries	Outcome
1	Leave tract 114100 alone	Combine tracts 114102 and 114101	Combine tracts 114102 and 114101	The boundaries for the specified tracts in 2010 and 2020 are set to equal the tract definition for 114100 in 2000
2	Leave tract 116300 alone	Combine tracts 116301 and 116302	Combine tracts 116301 and 116302	The boundaries for the specified tracts in 2010 and 2020 are set to equal the tract definition for 116300 in 2000
3	Leave tract 119100 alone	Combine tracts 119101 and 119102	Combine tracts 119101 and 119102	The boundaries for the specified tracts in 2010 and 2020 are set to equal the tract definition for 119100 in 2000
4	Combine tracts 103900 and 104100	Leave tract 126800 alone	Leave tract 126800 alone	The boundaries for the specified tracts in 2000 are set to equal the tract definition for 126800 in 2010 and 2020
5	Combine tracts 107100 and 107700	Leave 126900 alone	Leave 126900 alone	The boundaries for the specified tracts in 2000 are set to equal the tract definition for 126900 in 2010 and 2020
6	Combine tracts 108400 and 108500	Leave 127000 alone	Leave 127000 alone	The boundaries for the specified tracts in 2000 are set to equal the tract definition for 127000 in 2010 and 2020
7	Combine tracts 113100 and 113400	Leave tract 127200 alone	Leave tract 127200 alone	The boundaries for the specified tracts in 2000 are set to equal the tract definition for 127200 in 2010 and 2020

8	Combine tracts 117300 and 118500	Leave tract 127300 alone	Leave tract 127300 alone	The boundaries for the specified tracts in 2000 are set to equal the tract definition for 127300 in 2010 and 2020
9	Combine tracts 120100 and 120300	Leave 127100 alone	Leave 127100 alone	The boundaries for the specified tracts in 2000 are set to equal the tract definition for 127100 in 2010 and 2020
10	Combine tracts 121300 and 121400	Leave tract 127500 alone	Leave tract 127500 alone	The boundaries for the specified tracts in 2000 are set to equal the tract definition for 127500 in 2010 and 2020
11	Combine tracts 122100, 122200, and 122400	Leave tract 127400 alone	Leave tract 127400 alone	The boundaries for the specified tracts in 2000 are set to equal the tract definition for 127400 in 2010 and 2020
12	Combine tracts 123400 and 123500	Leave tract 127600 alone	Leave tract 127600 alone	The boundaries for the specified tracts in 2000 are set to equal the tract definition for 127600 in 2010 and 2020
13	Combine tracts 111400 and 111500	Combine tracts 111400 and 111500	Leave 127700 alone	The boundaries for the specified tracts in 2000 and 2010 are set to equal the tract definition for 127700 in 2020
13	Combine tracts 118400 and 121100	Combine tracts 118400 and 121100	Leave tract 127800 alone	The boundaries for the specified tracts in 2000 and 2010 are set to equal the tract definition for 127800 in 2020

As a result of standardizing the census tracts and creating the new reconstructed tracts with the key, the total number of geographic units declined across the three counties/cities. These are shown in Table A6. The primary reason the reconstructed tracts are fewer in number is because the majority of census tract changes typically involve the further dividing of preexisting census tracts into smaller tracts, meaning that most of the reconstructed tracts contain multiple preexisting census tracts that have been pieced back together.

Table A6.

Jurisdiction	Number of Distinct Pseudo-Tracts
El Paso County	123
Philadelphia	336
St. Louis	102

The reconstructed census tract keys were applied to our three datasets differently. The original tract boundaries change over time *differently* depending on the data source. First, before merging, we use our key to standardize the boundaries in each dataset separately. Then, we merge the three datasets together using the key-year as our merge link. For HMDA, the data records for years 2007-2011 follow 2000 census tract boundaries. The records for the years 2012-2021 follow 2010 census tract boundaries, and the records for the year 2022 use 2020 census tract boundaries. For ACS, data for 2009 follow 2000 boundaries, data for 2010-2019 use 2010 boundaries, and data for 2020-2022 follows 2020 boundaries. For CoreLogic, all data records follow 2020 census tract boundaries. These are summarized in Table A7 below.

Table A7. Tract Boundaries for Our Three Data Sources

Dataset	Year Range	Number of Years	Census Boundary Definition Set
HMDA	2007-2011	5	2000
HMDA	2012-2021	10	2010
HMDA	2022	1	2020
ACS	2009	1	2000
ACS	2010-2019	10	2010
ACS	2020-2022	3	2020
CoreLogic	2007-2022	16	2020

C. Cleaning and processing HMDA data[5]

HMDA's publicly available Modified Loan/Application Register (LAR) data for the years 2007-2022 were downloaded and appended. Only loan applications for the purposes of buying a home were retained, so refinance loan applications were dropped.[6] Only loan application records for the purposes of dwelling in a home were kept, so secondary homes and investment properties were excluded.[7] We only kept loan applications that were completed, which we define as loans that made it through the entire loan application process with a final decision made. The final outcome could be that the loan originated, it was approved but the applicant did not accept the loan, or it was denied.[8] This approach has been similarly used elsewhere (D'Acunto, and Rossi, 2022). Home improvement loan analyses were conducted separately.

Loan application records were retained for El Paso County, Philadelphia, and St. Louis. For the years 2007-2017, the census tract identifiers do not follow FIPS code convention, so these were reformatted to be the 11-digit FIPS code identifier. Only a very small percentage of loan records had missing census tracts (around 1 percent of all records).

Once these steps were implemented, the keys for our reconstructed tracts were merged onto the appended HMDA dataset. Furthermore, an additional categorical variable was merged onto the HMDA dataset, which categorized census tracts into 1 of 3 groups, which we designated as Distressed, Affluent, or Other (the methodology for defining these groups is described later in the Appendix).

Prior to aggregating HMDA data to the reconstructed-census-tract-year level, several variables were created, which are summarized below in Table A8.

Table A8. HMDA Variables Created Prior to Aggregation

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[5] For all charts that employed mortgage trends using HMDA data, we only included loans for which the primary intent was to "purchase and occupy a house." There is another variable, "type of lien," which could be first or second lien. For the paper's analysis, we did not exclude transactions where someone was buying a house with a second lien. In an analysis of the data, we found that for six data points (2004 vs. 2022, for all 3 cities), the average number of second liens used to purchase a house in order to occupy was 6.3 percent of all mortgages. When we excluded the second lien loans from the calculation of the average mortgage size, there was only an average difference of 4.5 percent across three cities and 18 years.

[6] Designated in HMDA data as *loan_purpose* equals 1 or 2.

[7] Designated in HMDA data as *owner_occupancy* equals 1 (in the 2007-2017 files) and *occupancy_type* equals 1 (in 2017-2022 files).

[8] Originated loan applications are designated in HMDA data as *action_taken* = 1, applications that was approved but the applicant did not accept
the loan are designated as *action_taken* = 2, and denied applications are designated as *action_taken* = 3.

Variable	Definition
Loan application purpose was to purchase	Equal 1 if the loan application record had loan_purpose = 1
Loan application for a purchase loan < $150,000	Equal 1 if the loan application record had loan_purpose = 1 and loan_amount < 150,000
Loan application for a purchase loan >= $150,000	Equal 1 if the loan application record had loan_purpose = 1 and loan_amount >= 150,000
Loan application purpose was to improve	Equal 1 if the loan application record had loan_purpose = 2 and lien_status = 1. So, this was an application for a first-lien home improvement loan
Originated purchase loan	Equal 1 if the loan application was originated (action_taken = 1), and the purpose was to buy a home (loan_purpose = 1)
Originated purchase loan for a loan < $150,000	Equal 1 if the loan application was originated (action_taken = 1), the purpose was to buy a home (loan_purpose = 1), and loan_amount < 150,000
Originated purchase loan for a loan >= $150,000	Equal 1 if the loan application was originated (action_taken = 1), the purpose was to buy a home (loan_purpose = 1), and loan_amount >= 150,000
Originated improvement loan	Equal 1 if the loan application was originated (action_taken = 1), and the purpose was for a home improvement (loan_purpose = 2)
Denied purchase loan	Equal 1 if the loan application was denied (action_taken = 3), and the purpose was to buy a home (loan_purpose = 1)
Denied purchase loan < 150,000	Equal 1 if the loan application was denied (action_taken = 3), the purpose was to buy a home (loan_purpose = 1), and loan_amount < 150,000
Denied purchase loan >= 150,000	Equal 1 if the loan application was denied (action_taken = 3), the purpose was to buy a home (loan_purpose = 1), and loan_amount >= 150,000

Denied improvement loan	Equal 1 if the loan application was denied (action_taken = 3), and the purpose was for a home improvement (loan_purpose = 2)

With the loan level variables in Table A8 created, we then aggregated (summed) the dataset to the reconstructed-tract-year level, and then calculated a set of new variables. These additional variables are summarized in the table below.

Table A9. HMDA Variables Created After Aggregation

Variables	Definition
V1	Count of completed loan applications in the tract for the purpose of purchasing a home to occupy
V2	Count of completed loan applications in the tract for the purpose of purchasing a home to occupy, where the loan amount was < $150,000
V3	Count of completed loan applications in the tract for the purpose of purchasing a home to occupy, where the loan amount was >= $150,000
V4	Count of completed loan applications in the tract for the purpose of improving a home
V5	Count of completed loan applications in the tract for the purpose of purchasing a home to occupy that were originated
V6	Count of completed loan applications in the tract for the purpose of purchasing a home to occupy that were originated where the loan amount was < $150,000
V7	Count of completed loan applications in the tract for the purpose of purchasing a home to occupy that were originated where the loan amount was >= $150,000
V8	Count of completed loan applications in the tract for the purpose of improving a home that were originated.
V9	Count of completed loan applications in the tract for the purpose of purchasing a home to occupy that were denied
V10	Count of completed loan applications in the tract for the purpose of purchasing a home to occupy that were denied where the loan amount was < $150,000
V11	Count of completed loan applications in the tract for the purpose of purchasing a home to occupy that were denied where the loan amount was >= $150,000
V12	Count of completed loan applications in the tract for the purpose of improving a home that were denied

Percent	
V13	Percentage of all completed purchase-loan applications in a tract that were originated [(#5/#1)*100]
V14	Percentage of all completed purchase-loan applications for loans < $150,000 in a tract that were originated [(#6/#2)*100]
V15	Percentage of all completed purchase-loan applications for loans >= $150,000 in a tract that were originated [(#7/#3)*100]
V16	Percentage of all completed improvement-loan applications for loans in a tract that were originated [(#8/4#)*100]
V17	Percentage of all completed purchase-loan applications in a tract that were denied [(#9/1#)*100]
V18	Percentage of all completed purchase-loan applications for loans < $150,000 in a tract that were denied [(#10/#2)*100]
V19	Percentage of all completed purchase-loan applications for loans >= $150,000 in a tract that were denied [(#11/#3)*100]
V20	Percentage of all completed improvement-loan applications for loans in a tract that were denied [(#12/#4)*100]
Rates	
V21	Count of completed loan applications in the tract for the purpose of purchasing a home to occupy, per 1,000 housing units in the tract
V22	Count of completed loan applications in the tract for the purpose of improving a home, per 1,000 owner-occupied housing units in the tract
V23	Count of completed loan applications in the tract for the purpose of purchasing a home where the loan amount was < $150,000, per 1,000 owner-occupied units valued < $150,000
V24	Count of completed loan applications in the tract for the purpose of purchasing a home where the loan amount was >= $150,000, per 1,000 owner-occupied units valued >= $150,000

An Important Note on Improvement Loans

The way lenders report home improvement loans changed during our study's time frame of 2007-2022, complicating the comparison of levels from year to year. In 2018, there was a change such that only improvement loans that were secured by a dwelling were to be reported under HMDA. Therefore, when comparing the number of improvement loans, there is likely to be a natural downward level-shift post-2018. To mitigate, but not fully correct, this issue, we only measure home improvement loans that are first-lien. This is not a perfect solution because a first-lien mortgage is simply secured with real estate, not necessarily the dwelling place where the borrower resides. This data is reported in

Appendix B but we do not highlight it in the “takeaway” section because of these definition changes.

D. Cleaning and processing CoreLogic data

To prepare CoreLogic data for analysis, we started by filtering the raw data for property sales records in El Paso County, Philadelphia, and St. Louis. We implemented several other filters, which we describe below.

- Keep only transaction records that involve residential properties, excluding commercial properties.[9]
  - Our focus is on the residential housing market, so we are not interested in examining commercial properties.
- Keep only transaction records that do not involve newly constructed properties.[10]
  - We are interested in examining the preexisting housing market. New construction is often sold by a home builder company. In many cases, newly built homes are built for a particular buyer, which is not necessarily a market transaction. Furthermore, if kept, these transactions would appear in the data as a possible investor selling a property.
- Keep only transaction records that do not involve short sales.[11]
  - Short sales are not market transactions, in the sense that the seller typically is facing financial hardship and chooses to sell the home for less than what is owed on the loan, with the mortgage lender often taking the earnings.
- Keep only transaction records that do not involve foreclosure sales.[12]
- Keep only transaction records that involve resales.[13]
  - We only want preexisting home sales.
- Keep only transaction records that do not involve transactions between family members.[14]
  - We do not want property transactions that involve family members as they are not considered true market transactions.
- Keep records that involve “arm’s length” transactions.[15]
- Only keep property types that we can confirm are types that households can live in. So for example, we do not want a boat port, or a barn, or a vacant lot. We keep

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[9] Designated in CoreLogic data as *residentialindicator* equals "Y".
[10] Designated in CoreLogic data as *Newconstructionindicator* equals 0.
[11] Designated in CoreLogic data as *shortsaleindicator* not equal to 0.
[12] Designated as *foreclosurereosaleindicator* equals 0, or *foreclosurereoindicator* equals 0.
[13] Designated as *resaleindicator* equals 1.
[14] Designated as *interfamilyrelatedindicator* equals 0.
[15] Designated as *primarycategorycode* not equal to “B” and not equal to “C”.

properties that are confirmed as single-family residential units, townhouses, and duplexes.[16]

Correcting for bulk transactions

Some transactions involve multiple properties, with the total sale amount of the bulk property being assigned to each individual property. To correct for this, we divide the total sale amount by the total number of properties in the transaction.

Correcting for outliers in sale price

Some sale amount values are extreme and clear outliers. This is not an immediate issue for us because we are primarily interested in counting the number of homes sold for prices that fall above or below a particular threshold ($200,000). However, it becomes an important issue to address when estimating the Fair Market Price (FMP) in a particular area. To address these outliers, we winsorize the sale amount using the sale amount - year distribution for each city/county. Specifically, for sale amounts that are in the bottom 1 percent of the city-year distribution, we replace them with the value designating the first percentile. For sale amounts that are above the 99th percentile, we replace them with the value designating the 99th percentile. We do the same for the property square footage variable, which also contains outliers.

External validation of CoreLogic data

After making these adjustments, at a high level, we use Zillow and Redfin data to externally validate our own data. It's important to note that we don't know Redfin's or Zillow's process for counting relevant home sales, so we should not expect the levels to be the same. However, we see similar trends with the data from Zillow and Redfin closely tracking the CoreLogic data as seen below in Figures A1-A3.

Figure A1. Home Sales in Philadelphia: Redfin vs. Our CoreLogic Sample

[16] These are defined as *landusecodestatic* equal to either 163, 102, 112, 115, or 100.

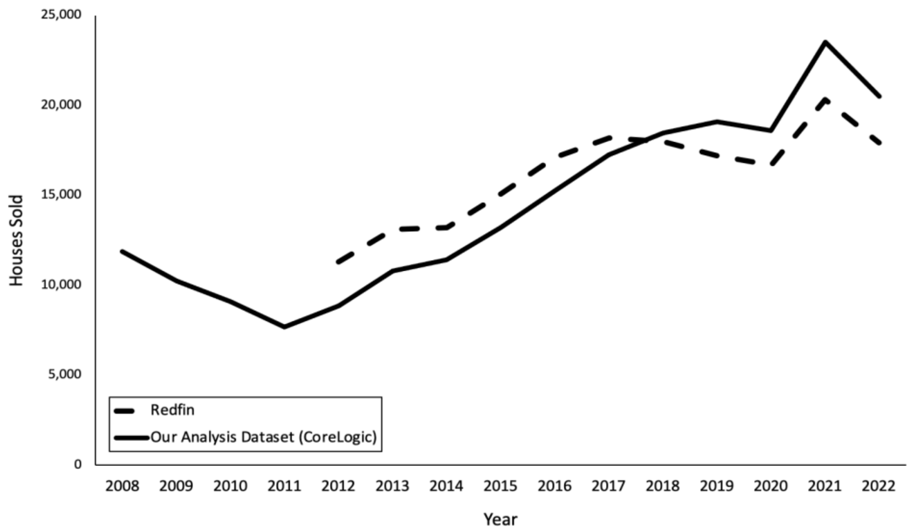


Figure A2. Home Sales in El Paso: Zillow vs. Our CoreLogic Sample

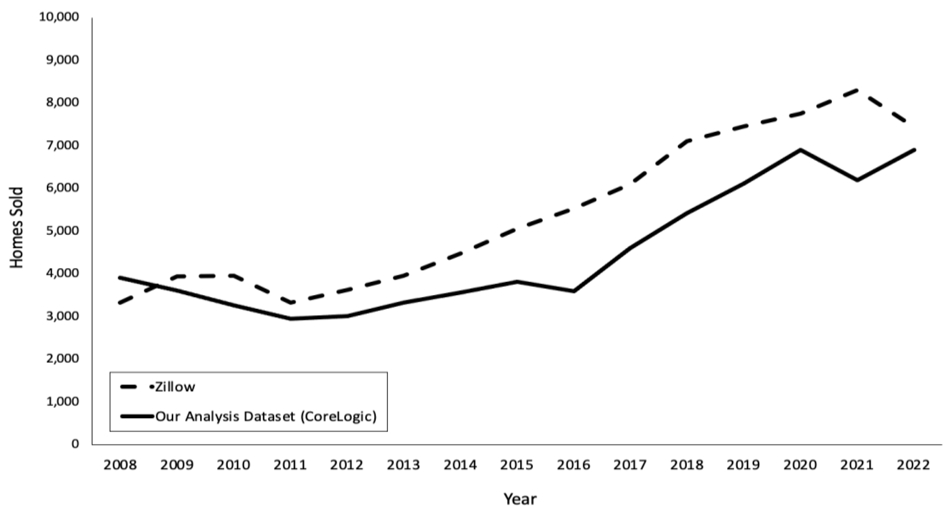
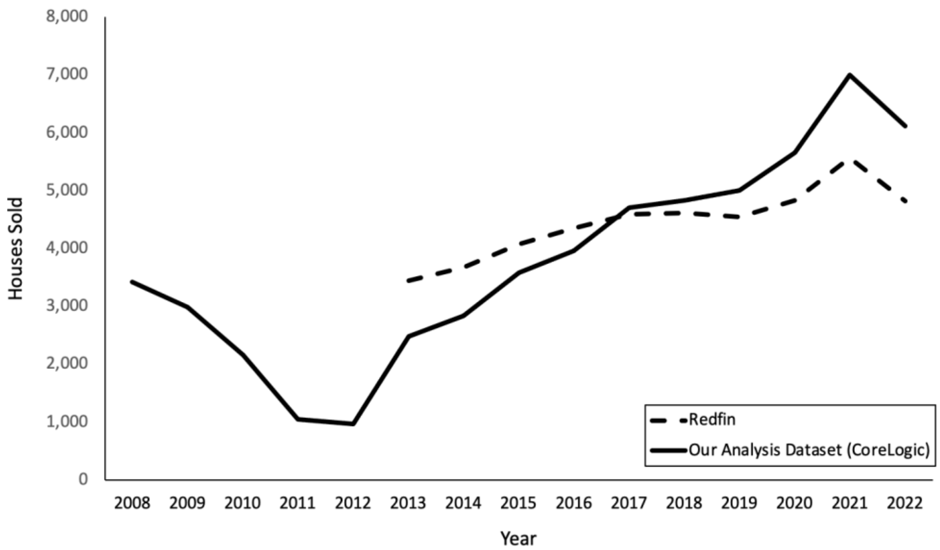


Figure A3. Home Sales in St. Louis County (City): Redfin vs. Our CoreLogic Sample



CoreLogic Special Cases and Limitations

As we stated earlier, there are instances of bulk purchases. These are instances where a seller (typically an investment company) sells multiple properties at once to a buyer. The entire sale amount of the bulk transaction is applied to every property in the bundle. To adjust this inflated price, we divide the total sale amount by the total number of properties in the bundle.

There are some clear outliers in the data. For example, there are transactions that involve sale amounts that are unbelievably low, and cases where they are unbelievably high. To correct our data, we winsorize our data by replacing sale amounts below the first percentile in a given year by the value designating the first percentile, and by replacing sale amounts above the 99th percentile of the distribution with the value that designates the 99th percentile. This will be especially important when we produce our market values.

Several limitations are worth highlighting. Some legitimate transactions are simply missing sale amount information, which makes these instances unusable. Cases like these are the exception, though. There are instances where a transaction involves a property that does not have an assigned census tract. Cases like these are the exception too. Approximately 5 percent of these cases fell into this category and were deleted.

CoreLogic Variables

CoreLogic provides several useful indicator variables that we rely on for our analysis, which are: 1) a binary variable indicating whether the buyer paid in cash or used a mortgage loan; 2) whether the buyer was a business; and 3) whether the buyer intends to live in the purchased property.

We merge our reconstructed census tract keys onto the transaction level dataset. Prior to converting CoreLogic data to a census-tract-year level, several variables were created from CoreLogic data, which are summarized below in Table A10.

Table A10. CoreLogic Variables Created Before Aggregation

Variable	Definition
Sale Amount < $200k	Equal to 1 if the sale amount of the property was less than $200,000
Sale Amount >= $200k	Equal to 1 if the sale amount of the property was $200,000 and over
Purchase Method Cash	Equals 1 if the buyer purchased the property with cash
Purchase Method Mortgage	Equals 1 if the buyer purchased the property with a mortgage loan
Cash Purchase, < $200k	Equal to 1 if the property was bought with cash and sale amount is less than $200,000
Cash Purchase, >= $200k	Equal to 1 if the property was bought with cash and sale amount is $200,000 or more
Mortgage Purchase, < $200k	Equal to 1 if the property was bought with a mortgage loan and sale amount is less than $200,000
Mortgage Purchase, >= $200k	Equal to 1 if the property was bought with a mortgage loan and sale amount is $200,000 or more
Business Purchase	Equal to 1 if the buyer is a business
Business Purchase, < $200k	Equal to 1 if the buyer is a business and the sale amount is less than $200,000
Business Purchase, >= $200k	Equal to 1 if the buyer is a business and the sale amount is $200,000 or more
Buyer Will Not Occupy	Equal to 1 if the buyer has no intention of occupying the property
Buyer Will Not Occupy, < $200k	Equal to 1 if the buyer has no intention of occupying the property and sale amount is < $200k

Buyer Will Not Occupy, >= $200k	Equal to 1 if the buyer has no intention of occupying the property and sale amount is >= $200k

With the transaction level variables in Table A10 created, we then aggregated (summed) the dataset to the reconstructed-census-tract-year level, and then calculated a set of additional variables. These are summarized in the table below.

Table A11. CoreLogic Variables Created After Aggregation

Variables	Definition
Counts	
#1	Count of the total number of homes involved in a buy/sell transaction in the tract
#2	Count of the total number of homes, bought for less than $200,000, involved in a buy/sell transaction in the tract
#3	Count of the total number of homes, bought for $200,000 or more, involved in a buy/sell transaction in the tract
#4	Count of the total number of homes involved in a buy/sell transaction where the buyer used cash, in the tract
#5	Count of the total number of homes involved in a buy/sell transaction where the buyer used a mortgage loan, in the tract
#6	Count of the total number of homes bought for less than $200,000 involved in a buy/sell transaction where the buyer used cash in the tract
#7	Count of the total number of homes bought for $200,000 or more involved in a buy/sell transaction where the buyer used cash in the tract
#8	Count of the total number of homes bought for less than $200,000 involved in a buy/sell transaction where the buyer used a mortgage loan in the tract
#9	Count of the total number of homes bought for $200,000 or more involved in a buy/sell transaction where the buyer used a mortgage loan in the tract
#10	Count of the total number of homes involved in a buy/sell transaction where the buyer was a business, in the tract
#11	Count of the total number of homes bought for less than $200,000 involved in a buy/sell transaction where the buyer was a business, in the tract
#12	Count of the total number of homes bought for $200,000 or more involved in a buy/sell transaction where the buyer was a business, in the tract

#13	Count of the total number of homes involved in a buy/sell transaction where the buyer will not occupy the dwelling, in the tract
#14	Count of the total number of homes bought for less than $200,000 involved in a buy/sell transaction where the buyer will not occupy the dwelling, in the tract
#15	Count of the total number of homes bought for $200,000 or more involved in a buy/sell transaction where the buyer will not occupy the dwelling, in the tract
Percent	
#16	Percentage of the total number of homes involved in a buy/sell transaction in the tract, where the buyer used cash [(#4/#1)*100]
#17	Percentage of the total number of homes involved in a buy/sell transaction in the tract, where the buyer used a mortgage loan [(#5/#1)*100]
#18	Percentage of the total number of homes involved in a buy/sell transaction bought for less than $200,000 in the tract, where the buyer used cash [(#6/#2)*100]
#19	Percentage of the total number of homes involved in a buy/sell transaction bought for $200,000 or more in the tract, where the buyer used cash [(#7/#3)*100]
#20	Percentage of the total number of homes involved in a buy/sell transaction bought for less than $200,000 in the tract, where the buyer used a mortgage loan [(#8/#2)*100]
#21	Percentage of the total number of homes involved in a buy/sell transaction bought for $200,000 or more in the tract, where the buyer used a mortgage loan [(#9/#3)*100]
#22	Percentage of the total number of homes involved in a buy/sell transaction in the tract, where the buyer was a business [(#10/#1)*100]
#23	Percentage of the total number of homes involved in a buy/sell transaction bought for less than $200,000 in the tract, where the buyer is a business [(#11/#2)*100]
#24	Percentage of the total number of homes involved in a buy/sell transaction bought for $200,000 or more in the tract, where the buyer used cash [(#12/#3)*100]
#25	Percentage of the total number of homes involved in a buy/sell transaction in the tract, where the buyer will not occupy the dwelling [(#13/#1)*100]

#26	Percentage of the total number of homes involved in a buy/sell transaction bought for less than $200,000 in the tract, where the buyer will not occupy the dwelling [(#14/#2)*100]
#27	Percentage of the total number of homes involved in a buy/sell transaction bought for $200,000 or more in the tract, where the buyer will not occupy the dwelling [(#15/#3)*100]
Rates	
#28	Count of the total number of homes involved in a buy/sell transaction where the buyer used cash, in the tract, per 1,000 housing units
#29	Count of the total number of homes bought for less than $200,000 involved in a buy/sell transaction where the buyer used cash, in the tract, per 1,000 owner-occupied units valued under $200,000
#30	Count of the total number of homes bought for $200,000 or more involved in a buy/sell transaction where the buyer used cash, in the tract, per 1,000 owner-occupied units valued at $200,000 and up
#31	Count of the total number of homes involved in a buy/sell transaction where the buyer was a business, in the tract, per 1,000 housing units
#32	Count of the total number of homes bought for less than $200,000 involved in a buy/sell transaction where the buyer was a business, in the tract, per 1,000 owner-occupied units valued under $200,000
#32	Count of the total number of homes bought for $200,000 or more involved in a buy/sell transaction where the buyer was a business, in the tract, per 1,000 owner-occupied units valued at $200,000 and up
#33	Count of the total number of homes involved in a buy/sell transaction where the buyer will not occupy the dwelling, in the tract, per 1,000 housing units
#34	Count of the total number of homes bought for less than $200,000 involved in a buy/sell transaction where the buyer will not occupy the dwelling, in the tract, per 1,000 owner-occupied units valued under $200,000
#35	Count of the total number of homes bought for $200,000 or more involved in a buy/sell transaction where the buyer will not occupy the dwelling, in the tract, per 1,000 owner-occupied units valued at $200,000 and up
Other	
#36	The fair market price (FMP), per square foot, of homes in the tract. This is calculated as the average sale price of homes that sold in the tract, divided by the average square footage of the homes that sold in the tract

Within CoreLogic's transaction data, there are instances of sales records that are missing a sale amount. We retain these records to make sure we still get an accurate estimate for the total number of homes sold. For example, when calculating the number of homes sold, we might have three mutually exclusive and exhaustive categories such as: 1) Homes Sold for < $200k, 2) Homes Sold for >= $200, and 3) Homes Sold but Sale Amount Missing.

An important note on El Paso

While examining our data, we noticed that very few sales in El Paso involved cash. The number is so low, in fact, that we do not think the data accurately describes the true level of cash transactions; therefore, we chose not to present cash-related measures sliced by amount for El Paso.

E. Cleaning and processing ACS data

Raw micro-level ACS five-year estimate data at the census tract level was downloaded from the Integrated Public Use Microdata Series (IPUMS) National Historical Geographic Information System (NHGIS) database maintained by the Minnesota Population Center at the Institute for Social Research & Data Innovation at the University of Minnesota. ACS five-year estimates are calculated using a rolling and weighted year sample for a window of five years. Each of the annual estimates, within the five-year window, are averaged to get the five-year estimate. Some researchers will use the middle year within the five-year window to represent that year's estimate (the estimates for the 2009-2013 five-year estimates would be assigned to year 2011, for example). Others (see Chetty, Hendren, Kline, and Saez, 2014) sometimes use the last year in the five-year window to represent that year's estimate (the estimates for the 2009-2013 five-year estimates would be assigned to year 2013, for example). Both have pros and cons, but we follow the latter approach because it enables us to avoid imputing values for the two most recent years (2021 and 2022). The year and the corresponding five-year estimates are shown in Table A12 below.

Table A12. ACS Years

Year	ACS 5-Year Estimate
2009	2005-2009
2010	2006-2010
2011	2007-2011
2012	2008-2012
2013	2009-2013
2014	2010-2014
2015	2011-2015

2016	2012-2016
2017	2013-2017
2018	2014-2018
2019	2015-2019
2020	2016-2020
2021	2017-2021
2022	2018-2022

The five-year estimates for the years 2009 through 2022 were downloaded and appended, with our reconstructed census tract keys then being merged onto the ACS data. These data were then aggregated (summed and in one case averaged) to our key's level. Table A13 below contains the variables we created using the ACS data.

Table A13. ACS Variables

Variables	**Definition**
Percent	
#1	Percentage of total households in the tract below the federal poverty line (poverty rate)
#2	Percentage of total households in the tract on SNAP/food stamps
#3	Percentage of occupied housing units that are owner-occupied (homeownership rate)
#4	Percentage of total housing units that are unoccupied/vacant (vacancy rate)
#6	Percentage of total housing units with incomplete plumbing
#7	Percentage of total housing units with incomplete kitchens
#8	Percentage of owner-occupied housing units that are valued below $150,000
#9	Percentage of total housing units that are single-family detached units
#10	Percentage of total housing units that are single-family attached units
#11	Percentage of total housing units that are multifamily units
#12	Percentage of total housing units that are mobile units
#13	Percentage of total housing units that are all other structural types
#14	Percentage of the total population that is non-Hispanic White
#15	Percentage of the total population that is non-Hispanic Black
#16	Percentage of the total population that is non-Hispanic Asian

#17	Percentage of the total population that is Hispanic
#18	Percentage of the total population less than 18 years old
#19	Percentage of the total population 18 - 25 years old
#20	Percentage of the total population 25 - 65 years old
#21	Percentage of the total population 65 and older years old
#22	Percentage of the population, 25 years old and older, with less than a high school level education
#23	Percentage of the population, 25 years old and older, with more than just a four-year college level education
#24	Percentage of all commuters with commutes over 60 minutes
#25	Percentage of the employed labor force employed in the agriculture forestry, fishing, hunting, or mining industries
#26	Percentage of the employed labor force employed in the construction industry
#27	Percentage of the employed labor force employed in the manufacturing industry
#28	Percentage of the employed labor force employed in the wholesale trade industry
#29	Percentage of the employed labor force employed in the retail trade industry
#30	Percentage of the employed labor force employed in the transportation, warehousing, or administration industries
#31	Percentage of the employed labor force employed in the information industry
#32	Percentage of the employed labor force employed in the finance, insurance, or real estate industries
#33	Percentage of the employed labor force employed in the professional, scientific, waste management, or administration industries
#34	Percentage of the employed labor force employed in the education services, healthcare, or social services industries
#35	Percentage of the employed labor force employed in the arts, entertainment, recreation, or accommodations industries
#36	Percentage of the employed labor force employed in other services industries
#37	Percentage of the employed labor force employed in public administration industry
#38	Percentage of total households with an internet subscription

#39	Percentage of total households with no internet access
#40	Percentage of total households with a mobile smartphone
#41	Percentage of total households with a computer
#42	Percentage of total households with at least 1 computing device
#43	Percentage of the population, 16 years old and older, in the labor force (Labor force participation rate)
#44	Percentage of the total labor force that is unemployed (Unemployment rate)
#45	Percentage of the population, at least 1 year old, that lived in the same house 1 year ago
#46	Percentage of the population, at least 1 year old, that lived elsewhere 1 year ago
#47	Percentage of the population, at least 1 year old, that outside of the U.S. 1 year ago
#48	Percentage of total households with at least one vehicle
#49	Percentage of total households with no vehicles
#50	Percentage of the population, 25 to 54 years old, who work full time
#51	Percentage of the population, 25 to 54 years old, who work part time
#52	Percentage of the population, 25 to 54 years old, who did not work at all in the past year
Mean	
#	Total aggregated income divided by the total population (Income per capita)

As was stated before, our final analysis dataset ranges from 2007 to 2022. However, ACS five-year estimate data is only available from 2009 to 2022, which means we do not have data for 2007 and 2008. We impute values for 2007 and 2008 by extrapolating back the average annual change, for each reconstructed census tract, from 2009 to 2013. To illustrate, for the variable Population, we calculate the annual change in Population from 2009 to 2010, 2010 to 2011, 2011 to 2012, and 2012 to 2013. Then, we would take the mean of these calculated changes. To impute the value for 2008, we take the reconstructed tract's Population in 2009 and subtract the mean change. Then, to get the value for 2007, we subtract the mean change from the 2008 value just calculated. In this way, we can maintain recent trends.

F. A note on nominal housing values vs. real housing values

The use of nominal numbers for this research was chosen for a few key reasons. First, calculating a real house price index involves many subjective decisions and assumptions that can create distortions of their own, especially when using the CPI as an adjustment method, since housing is both a consumption good and an asset good, as noted by Bernstein et. al (2021) in "Housing Prices and Inflation" (2021). He notes, "... the price of a house reflects both its value as an investment asset, which CPI in principle wants to ignore, and as a good that provides a 'service' — shelter — to the families that live in it, whose cost CPI wants to incorporate." In other words, rising house prices create wealth as well as higher living expenditures simultaneously, which makes "correcting for inflation" using the various indexes far more thorny for houses than for pure consumption items, such as grocery store items.

By choosing to use nominal prices despite the ongoing housing appreciation issues, it is much easier to see up front the potential price distortions rather than having them buried under a set of assumptions that create distortions of their own. In addition, it would mean that not only would housing prices need to be adjusted, so would the yearly definition of a small-dollar mortgage. This makes explication even more difficult to a wider audience.

In addition, the advantage of using nominal values is the ability to more easily modify and adjust if needed to make desired inflation corrections in a later report, on say a geographical or time series approach. Our early discussions with the Pew team resulted in agreement upon this approach.

A better approach of indicating housing affordability as well as housing inflation is to create a variable that measures the buying power of the area median wage, an approach taken by Harvard's Joint Center for Housing Studies. Housing affordability can be measured by taking the median house price divided by median wages in the same geographic area, in time t, both in nominal terms. This creates an index that measures the purchasing power of wages in a given time frame and locality without making any assumptions that create inevitable distortions in interpretation.

For this reason, we conduct a similar analysis in this report that shows the trends in housing affordability in each designated area (Distressed, Affluent, and All Other) using the average selling price of houses divided by the per capita income in time t.

G. Categorizing census tracts into designated areas

To better facilitate our descriptive analyses, we grouped census tracts together so that we could create higher-level visualizations at these levels, as discussed earlier in section III.B. We created a prosperity index, which averaged the poverty rate and the percentage of housing below $150,000 in each census tract. From there, we found contiguous areas that had high concentrations of poverty and affluence. We created three groups, which are 1) Distressed area, 2) Affluent area, and 3) All Other area. Figure A4 shows the resulting poverty rate calculations across these three groups, for each of our three counties/cities. Figure A5 shows the resulting share of low-value housing stock calculations across these three groups, for each of our three counties/cities.

Figure A4. Poverty Rates by Group in the 3 Cities

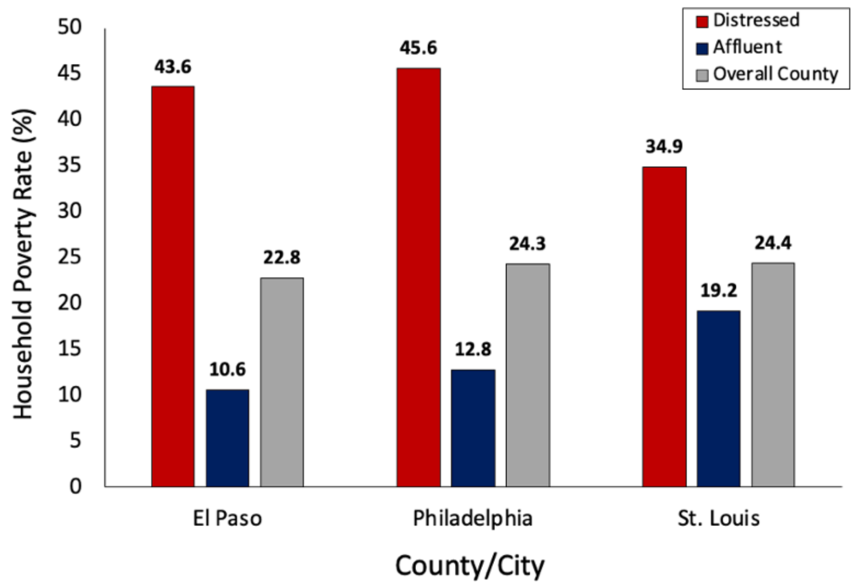


Figure A5. Low-Value Housing Stock by Group in the 3 Cities

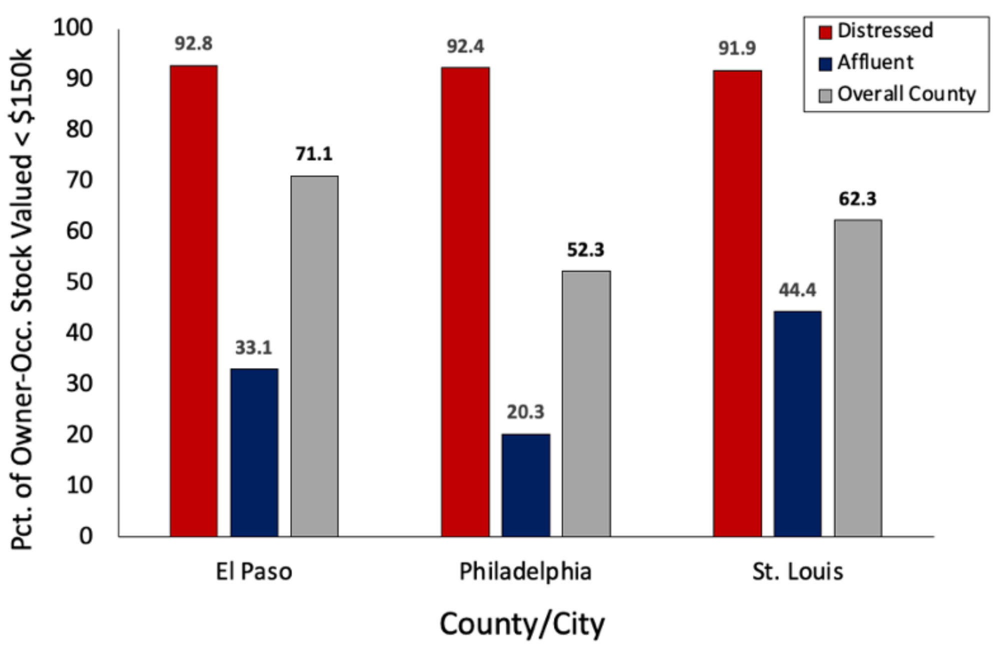
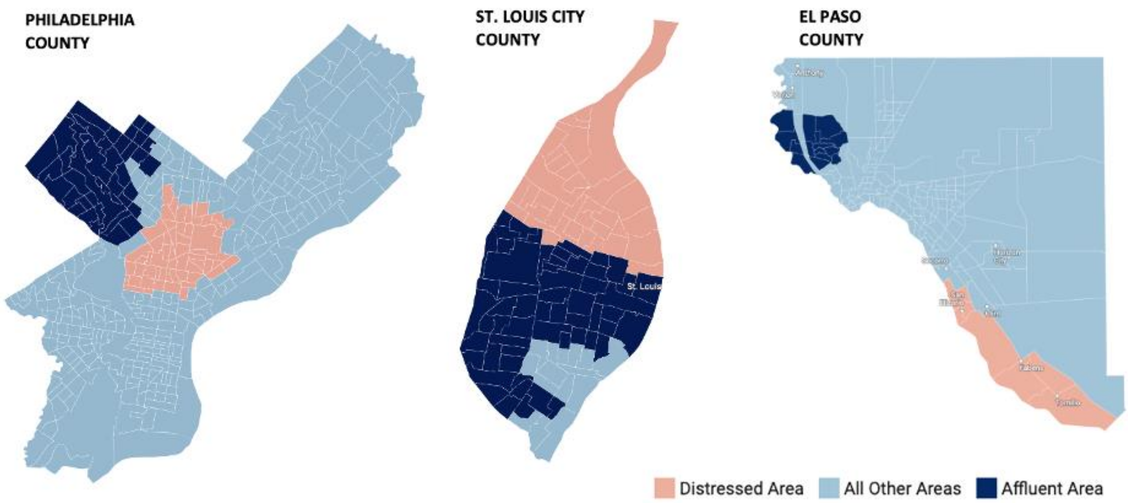


Figure A6 shows 2010 census tract boundary maps for the three cities. In Philadelphia, the Affluent tracts tend to cluster in the northwestern corner of the city, with Distressed tracts clustering in the city center. In St. Louis, the Affluent tracts tend to cluster in the southern half of the city, with Distressed tracts clustering in the northern half. In El Paso, the Affluent tracts tend to cluster in the northwestern corner of the city, with Distressed tracts clustering along the southern edge of the city.

Figure A6



Appendix B. El Paso: Descriptive Statistics

A. ACS demographic, migration, and economic data

EL PASO CITY	Distressed		Affluent		Other		Overall	
	2007	2022	2007	2022	2007	2022	2007	2022
AMERICAN COMMUNITY SURVEY (ACS) 5-YEAR ESTIMATES								
Demographic data (% of total population)								
Non-Hispanic Black	0.00	0.05	1.38	1.29	2.68	3.17	2.44	2.85
Non-Hispanic White	2.04	3.00	36.67	22.26	11.77	10.05	14.29	11.23
Non-Hispanic Asian	0.97	0.26	2.84	2.24	0.97	0.99	1.19	1.11
Non-Hispanic Other	2.09	0.72	0.26	2.60	0.92	1.82	0.88	1.86
Hispanic	94.90	95.97	58.85	71.61	83.66	83.97	81.20	82.95
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Less than 18 years old	37.21	29.97	30.35	23.69	32.79	26.78	32.66	26.53
19-25 years old	11.19	11.08	9.16	10.05	10.64	11.73	10.49	11.51
25-65 years old	43.98	45.36	50.65	52.03	45.93	49.22	46.41	49.42
65+ years old	7.62	13.59	9.84	14.23	10.64	12.26	10.44	12.54
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Male	49.71	49.48	45.49	49.55	48.04	49.8	47.81	49.76
Female	50.29	50.52	54.51	50.45	51.96	50.20	52.19	50.24
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Total Population	23,392	30,233	78,692	100,974	585,503	732,625	687,587	863,832
Migration (% of the population, at least 1 year old)								
Lived in the same house 1 year ago	100.00	88.91	80.83	85.87	85.32	86.87	85.36	86.82
Lived elsewhere 1 year ago	0.87	8.86	6.89	4.92	4.69	5.45	4.82	5.50
Lived outside of the U.S. 1 year ago	0.29	0.19	1.93	0.89	1.25	0.93	1.30	0.90
Population at least 1 year old	22,734	29,712	77,540	100,061	573,955	721,895	674,229	851,668
Economic data								
Income per capita ($)	8,343	17,563	26,808	43,256	13,733	23,982	15,046	26,010
Percent of households below the federal poverty line	37.96	22.56	14.03	11.1	27.66	21.4	26.21	20.12
Percent of households on SNAP/food stamps	20.48	36.84	6.96	7.20	19.89	22.09	18.27	20.65
Percent with at least 1 vehicle	97.95	93.97	93.98	95.94	89.64	93.14	90.42	93.52
Total Households	5,973	8,953	28,296	37,209	189,493	246,418	223,762	295,580

(El Paso, continued)

B. ACS industry and labor force data

	Distressed		Affluent		Other		Overall	
	2007	2022	2007	2022	2007	2022	2007	2022
Industry of Employment (% of employed people)								
Agriculture, Forestry, Fishing, Hunting, or Mining	3.40	4.12	0.76	1.08	0.76	1.00	0.84	1.12
Construction	17.00	10.90	2.34	4.69	7.89	7.67	7.45	7.38
Manufacturing	16.01	9.49	11.59	7.01	10.39	6.62	10.72	6.77
Wholesale Trade	4.22	3.51	3.66	2.95	3.33	2.35	3.40	2.47
Retail Trade	9.29	9.07	10.14	9.65	12.44	12.19	12.04	11.75
Transportation, Warehousing, or Utilities	10.14	10.67	5.16	4.60	7.16	7.40	6.99	7.14
Information	2.60	1.97	3.96	1.13	3.96	1.55	3.91	1.50
Finance, Insurance, or Real Estate	0.10	2.47	7.60	5.94	4.96	4.68	5.15	4.77
Professional, Scientific, Waste Management, or Administration	4.66	8.34	9.44	12.29	7.76	10.53	7.88	10.69
Education Services, Healthcare, or Social Services	16.65	23.96	28.42	31.29	21.94	25.37	22.62	26.11
Arts, Entertainment, Recreation, or Accomodations	8.85	6.71	7.19	8.67	7.71	9.60	7.67	9.38
Other Services	3.47	6.06	4.10	3.17	5.65	4.43	5.38	4.32
Public Administration	3.60	2.73	5.63	7.53	6.07	6.60	5.93	6.60
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Total Employed Persons	8,427	12,407	35,023	49,356	223,921	306,557	267,370	368,320
Labor Force Participation (% of the Population at Least 16 years old)								
In the labor force	58.77	57.53	64.85	65.90	59.20	62.35	59.85	62.62
Not in the labor force	41.23	42.47	35.15	34.10	40.80	37.65	40.15	37.38
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Population at least 16 years old	15,353	22,444	57,085	79,703	412,639	558,564	485,076	660,711
Unemployment (% of the labor force unemployed)								
Unemployed	3.99	2.16	2.98	3.07	4.09	4.29	3.96	4.07
Employed	96.01	97.84	97.02	96.93	95.91	95.71	96.04	95.93
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Population, 16 and up, in the labor force	9,023	12,912	37,020	52,524	244,282	348,265	290,318	413,737
Usual Hours Worked (% of the population, 25-54)								
Employed Part-Time**	28.77	28.45	22.94	20.91	22.35	21.68	22.65	21.81
Employed Full-Time**	41.61	52.84	61.92	64.09	55.54	58.81	55.90	59.25
Not Employed**	29.62	18.71	15.14	15.00	22.11	19.51	21.45	18.94
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Persons, Age 25-54 **	7,612	8,912	35,645	34,631	208,689	229,033	251,946	273,476
Commute to work (% of commuters)								
Commute is over 1 hour	4.32	9.34	2.05	4.34	2.79	3.89	2.74	4.13
Commute is less than 1 hour	95.68	90.66	97.95	95.66	97.21	96.11	97.26	95.87
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Commuters	7,949	11,482	33,015	43,536	215,971	297,464	256,934	352,482

(El Paso, continued)

C. ACS technology, education, and housing stock data

	Distressed		Affluent		Other		Overall	
	2007	2022	2007	2022	2007	2022	2007	2022
Technology Access (% of households)								
With an internet subscription*	60.59	84.85	85.74	89.77	70.11	86.03	71.85	86.47
With no internet access*	33.96	13.66	12.07	7.25	25.78	11.14	24.24	10.72
With a mobile smartphone*	66.85	91.94	79.63	92.58	66.48	87.78	68.19	88.52
With a computer*	55.19	52.98	85.81	85.84	67.29	70.89	69.33	72.24
With at least 1 computing device*	76.96	94.98	92.82	95.72	80.89	91.75	82.32	92.35
Total Households*	7,708	8,953	34,045	37,209	221,447	246,418	263,200	292,580
Education Attainment (% of the population 25 years old and older								
Less than a high school education	59.85	36.02	11.49	7.88	34.80	21.14	32.73	19.97
High school diploma or GED	24.34	30.10	17.99	15.97	24.93	25.29	24.07	24.29
Some college or Associates degree	12.95	23.85	26.08	25.87	25.94	31.72	25.56	30.72
Bachelors degree	1.83	7.63	27.01	30.46	9.71	15.23	11.58	16.88
Masters degree or higher	1.25	2.40	17.43	19.81	4.73	6.62	6.17	8.13
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Population 25 Years Old and Older	12,071	17,823	47,601	66,906	331,194	450,444	390,866	535,173
Housing Stock data (% of total housing units)								
Vacant units	6.32	10.19	7.58	8.26	7.84	7.76	7.77	7.90
Single-family detached units	67.42	56.15	71.88	69.5	65.25	62.78	66.15	63.43
Single-family attached units	1.44	3.07	5.53	3.71	3.84	3.85	3.99	3.80
Multi-family units	4.02	10.22	19.49	16.13	25.35	20.47	24.05	19.59
Other-type units (mobile homes, etc.)	27.12	30.56	3.10	10.66	5.56	12.90	5.81	13.18
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Incomplete plumbing	0.01	4.33	0.49	0.61	1.37	1.70	1.23	1.65
Incomplete kitchen	0.36	2.99	0.57	1.18	1.26	2.25	1.15	2.14
Total Housing Units	6,375	9,969	30,616	40,561	205,163	267,135	242,155	317,655

(El Paso, continued)

D. ACS housing unit data, owners vs. renters

	Distressed		Affluent		Other		Overall	
	2007	2022	2007	2022	2007	2022	2007	2022
Occupied Housing Unit Data (% of total occupied housing units)								
Percent of occupied housing units that are owner-occupied	87.64	77.16	74.42	70.03	63.55	61.43	65.56	63.00
Percent of occupied housing units that are renter-occupied	12.36	22.84	25.58	29.97	36.45	38.57	34.44	37.00
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Total Occupied Housing Units	5,973	8,953	28,296	37,209	189,493	246,418	223,762	292,580
Owner-Occupied Housing Unit Data (% of total owner-occupied housing units)								
Valued < $150.000	93.51	78.59	44.88	12.78	86.39	52.85	80.70	48.15
Valued $150,000 - $200,000	2.84	13.75	21.62	22.28	7.45	22.99	9.31	22.54
Valued $200,000 - $300,000	2.63	5.88	19.77	31.72	4.27	17.25	6.43	18.87
Valued $300,000 - $400,000	1.02	1.14	7.17	17.66	0.95	4.05	1.84	5.87
Valued $400,000 - $500,000	0.00	0.38	3.90	7.89	0.39	1.40	0.88	2.28
Valued $500,000 and Over	0.00	0.26	2.65	7.67	0.55	1.46	0.83	2.29
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Valued < $200,000	96.36	92.34	66.51	35.06	93.84	75.84	90.01	70.70
Valued $200,000 and Over	3.64	7.66	33.49	64.94	6.16	24.16	9.99	29.30
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Total Owner-Occupied Housing Units	5,234	6,908	21,058	26,059	120,417	151,371	146,709	184,338
Renter-Occupied Housing Unit Data (% of total owner-occupied housing units)								
Percent of renter households that are burdened (30% of more of their monthly income spent on rent)	38.59	36.04	49.51	42.16	48.52	48.27	48.52	47.41
Percent of renter households that are extremely burdened (50% of more of their monthly income spent on rent)	20.51	18.34	28.76	18.52	23.37	23.3	23.85	22.72
Total Renter-Occupied Housing Units	738	2,045	7,238	11,150	69,076	95,047	77,053	108,242

(El Paso, continued)

E. HMDA data on loan applications, denials, and originations

HOME MORTGAGE DISCLOSURE ACT (HMDA)	Distressed		Affluent		Other		Overall	
	2007	2022	2007	2022	2007	2022	2007	2022
Total Home-Purchase Loan Applications (% of completed home-purchase loan applications)								
Originated	43.03	66.29	74.83	91.00	57.39	86.55	65.90	88.93
Denied	44.48	29.21	15.09	5.89	32.68	9.65	23.63	7.76
Approved, but not accepted	12.49	4.50	10.08	3.11	9.93	3.80	10.47	3.31
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Total Home-Purchase Loan Applications	1,169	178	4,208	2,732	1,279	684	6,656	3,594
Total Home-Purchase Loan Applications for Loans Under $150k (% of completed home-purchase loan applications for loans under $150k)								
Originated	43.84	63.83	75.58	86.49	58.86	83.86	63.78	82.15
Denied	44.66	31.21	14.13	9.59	31.34	12.97	25.52	14.04
Approved, but not accepted	11.50	4.96	10.29	3.92	9.80	3.17	10.70	3.81
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Total Home-Purchase Loan Applications, Under $150k	1,104	141	2,428	459	1,123	347	4,655	947
	Distressed		Affluent		Other		Overall	
	2007	2022	2007	2022	2007	2022	2007	2022
Total Home-Purchase Loan Applications for Loans $150k and Over (% of completed home-purchase loan applications for loans $150k and over)								
Originated	46.15	75.68	73.82	91.90	46.79	89.32	70.81	91.35
Denied	41.54	21.62	16.40	5.15	42.31	6.23	19.24	5.52
Approved, but not accepted	12.31	2.70	9.78	2.95	10.90	4.45	9.95	3.13
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Total Home-Purchase Loan Applications, $150k and Over	65	37	1,780	2,273	156	337	2,001	2,647
Total Originated Home-Purchase Loans (% of originated completed home-purchase loan applications)								
Less than $150,000	94.04	76.27	58.27	15.97	90.05	49.16	67.69	24.34
$150,000 to $200,000	3.18	16.10	21.02	23.37	6.81	27.03	16.60	23.78
$200,000 to $250,000	2.78	6.78	10.64	19.03	1.91	8.95	8.28	16.71
$250,000 to $300,000	0.00	0.85	4.29	12.95	0.82	6.25	3.21	11.26
$300,000 to $350,000	0.00	0.00	2.22	10.58	0.14	4.22	1.62	9.01
$350,000 to $400,000	0.00	0.00	1.27	6.64	0.27	2.03	0.96	5.54
$400,000 to $450,000	0.00	0.00	0.89	3.70	0.00	0.84	0.64	3.04
$450,000 to $500,000	0.00	0.00	0.16	2.29	0.00	0.51	0.11	1.88
$500,00 and Over	0.00	0.00	1.24	5.47	0.00	1.01	0.89	4.44
Missing	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Total Originated Home-Purchase Loans	503	118	3,149	2,486	734	592	4,386	3,196

(El Paso, continued)

F. CoreLogic data on housing sales and prices

CORELOGIC data	Distressed		Affluent		Other		Overall	
	2007	2022	2007	2022	2007	2022	2007	2022
Housing Affordability								
Fair Market Price for the Average Home ($)	62,497	172,321	227,189	349,623	141,384	220,394	159,871	240,737
Percentage change, 2007-2020		*175.7%*		*53.9%*		*55.9%*		*50.6%*
Per capita income (ACS data)	$8,343	$17,563	$26,808	$43,256	$13,733	$23,982	$15,046	$26,010
Percentage change, 2007-2020		*110.5%*		*61.4%*		*74.6%*		*72.9%*
Yrs. to Purchase Home (Avg. area price/per cap. income)	7.49	9.81	8.47	8.08	10.30	9.19	10.63	9.26
Percentage change, 2007-2020		*31.0%*		*-4.6%*		*-10.7%*		*-12.9%*
Fair Market Price Per Square foot ($)	40.72	101.51	105.90	149.88	87.85	127.06	92.47	131.50
Percentage change, 2007-2020		*149.3%*		*41.5%*		*44.6%*		*42.2%*
Homes Bought/Sold (% of all homes bought/sold)								
Less than $200,000	36.69	25.10	37.49	6.61	58.85	26.57	54.01	23.41
$200,000 to $250,000	0.00	7.41	13.27	8.58	4.98	15.80	6.59	14.50
$250,000 to $300,000	0.00	1.23	9.39	10.61	2.17	8.07	3.61	8.33
$300,000 to $350,000	0.00	0.41	5.73	8.00	1.15	3.95	2.07	4.51
$350,000 to $400,000	0.00	0.82	3.93	7.14	0.60	1.90	1.27	2.70
$400,000 to $450,000	0.00	0.00	2.14	5.38	0.16	0.93	0.57	1.61
$450,000 to $500,000	0.00	0.00	1.24	3.36	0.13	0.53	0.36	0.96
$500,000 and Over	0.00	0.82	2.25	9.38	0.40	0.80	0.78	2.15
Missing Sale Amount ($) Information	63.31	64.20	24.56	40.94	31.65	41.49	30.81	41.87
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Bought with cash	62.72	62.12	24.51	39.18	31.63	40.00	30.77	40.32
Bought with mortgage	37.28	36.21	75.38	60.55	68.31	59.62	69.16	59.29
Unknown	0.00	1.67	0.11	0.27	0.06	0.39	0.07	0.39
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Bought by a business	3.55	7.41	15.03	28.31	6.81	14.73	7.28	14.43
Bought by a non-business (Person, or couple)	96.45	92.59	84.97	71.69	93.19	85.27	92.72	85.57
Unknown	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Buyer will not occupy	11.83	32.51	21.14	25.85	26.17	29.41	24.85	28.92
Buyer will occupy	33.73	45.27	75.83	72.71	67.99	68.48	68.94	68.67
Unknown	54.44	22.22	3.04	1.44	5.94	2.16	6.29	2.45
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Total Homes Bought/Sold	169	243	1,779	1,876	6,683	9,833	8,631	11,952

(El Paso, continued)

	Distressed		Affluent		Other		Overall	
	2007	2022	2007	2022	2007	2022	2007	2022
Homes Bought by a Business (% of all homes bought by a business)								
Less than $200,000	16.67	22.22	10.18	6.95	25.05	17.75	21.02	16.17
$200,000 and Over	0.00	0.00	4.79	13.51	5.49	8.08	5.25	8.81
Missing Sale Amount ($) Information	83.33	77.78	85.03	79.54	69.45	74.17	73.73	75.01
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Total Homes Bought by Business	6	18	167	259	455	1,448	628	1,725
Homes Bought Without the Intention to Occupy (% of all homes bought without the intention to occupy)								
Less than $200,000	45.00	22.78	27.93	7.42	41.34	20.71	39.02	18.89
$200,000 and Over	0.00	1.27	18.35	26.19	4.86	10.75	7.18	12.70
Missing Sale Amount ($) Information	55.00	75.95	53.72	66.39	53.80	68.53	53.80	68.40
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Total Homes Bought Without the Intention to Occupy	20	79	376	485	1,749	2,892	2,145	3,456
Homes with Cash (% of all homes bought with cash)								
Less than $200,000	0.00	0.00	0.23	0.00	0.66	0.05	0.56	0.04
$200,000 and Over	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Missing Sale Amount ($) Information	100.00	100.00	99.77	100.00	99.34	99.94	99.43	99.96
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Total Homes Bought With Cash	106	151	436	735	2,114	3,933	2,656	4,819

NOTES

* These variables only have available data for years after 2016. So, in the columns for **2007**, for these variables, the year measured is 2017.

** These variables only have available data for years after 2013. So, in the columns for **2007**, for these variables, the year measured is 2014.

For ACS data, excluding the technology and hours-worked variables, the 2007 estimates were linearly extrapolated back from 2009.

Appendix C. Philadelphia: Descriptive Statistics

A. ACS demographic, migration, and economic data

	PHILADELPHIA							
	Distressed		Affluent		Other		Overall	
	2007	2022	2007	2022	2007	2022	2007	2022
AMERICAN COMMUNITY SURVEY (ACS) 5-YEAR ESTIMATES								
Demographic data (% of total population)								
Non-Hispanic Black	57.36	49.89	34.60	36.33	39.74	37.27	41.90	38.95
Non-Hispanic White	7.38	6.48	60.58	50.81	45.86	36.67	41.39	33.54
Non-Hispanic Asian	2.16	3.29	1.62	2.48	6.00	8.77	5.15	7.54
Non-Hispanic Other	1.85	2.36	0.67	5.22	1.13	4.56	1.20	4.30
Hispanic	31.25	37.98	2.53	5.16	7.28	12.74	10.37	15.67
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Less than 18 years old	32.43	26.26	15.94	16.01	24.20	21.18	24.80	21.50
19-25 years old	11.07	11.78	8.49	8.74	9.40	9.91	9.58	10.08
25-65 years old	47.53	49.47	62.10	57.77	52.85	54.96	52.73	54.41
65 + years old	9.01	12.48	13.68	17.49	13.57	13.95	12.93	14.01
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Male	46.81	46.88	44.61	47.12	46.64	47.67	46.53	47.52
Female	53.19	53.12	55.39	52.88	53.38	52.33	53.49	52.48
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Total Population	217,679	221,086	105,179	118,733	1,205,458	1,253,389	1,528,316	1,593,208
Migration (% of the population, at least 1 year old)								
Lived in the same house 1 year ago	85.82	86.19	84.25	84.90	86.72	86.22	86.43	86.12
Lived elsewhere 1 year ago	3.05	2.97	5.62	7.41	3.67	4.41	3.71	4.43
Lived outside of the U.S. 1 year ago	0.38	0.45	0.38	0.53	0.73	0.79	0.66	0.73
Population at least 1 year old	213,384	218,246	103,991	117,330	1,188,994	1,238,447	1,506,368	1,574,023
Economic data								
Income per capita ($)	10,940	18,489	32,637	53,139	20,763	36,896	20,181	35,552
Percent of households below the federal poverty line	41.79	38.31	9.80	10.95	19.02	20.03	21.12	21.57
Percent of households on SNAP/food stamps	27.91	52.82	4.61	10.10	10.78	23.56	12.42	26.12
Percent with at least 1 vehicle	48.46	57.65	83.66	86.54	68.43	72.55	67.17	71.85
Total Households	70,053	83,077	45,430	55,477	444,584	520,575	560,067	659,129

B. ACS industry and labor force data

	Distressed		Affluent		Other		Overall	
	2007	2022	2007	2022	2007	2022	2007	2022
Industry of Employment (% of employed people)								
Agriculture, Forestry, Fishing, Hunting, or Mining	0.65	0.59	0.21	0.29	0.26	0.18	0.29	0.23
Construction	5.90	5.09	5.21	3.32	4.69	3.99	4.86	4.04
Manufacturing	10.81	6.26	7.27	6.62	8.03	6.34	8.24	6.36
Wholesale Trade	2.99	1.53	1.93	1.78	2.86	1.92	2.79	1.87
Retail Trade	8.29	12.69	7.03	7.71	9.93	9.03	9.50	9.28
Transportation, Warehousing, or Utilities	8.37	8.05	4.95	4.25	6.19	6.16	6.30	6.18
Information	1.90	0.68	2.87	2.54	2.57	2.01	2.53	1.92
Finance, Insurance, or Real Estate	4.77	2.70	8.42	8.43	7.37	6.69	7.20	6.45
Professional, Scientific, Waste Management, or Administration	8.71	9.56	13.42	15.47	10.88	12.49	10.89	12.46
Education Services, Healthcare, or Social Services	25.29	33.00	32.46	32.65	26.44	32.28	26.87	32.39
Arts, Entertainment, Recreation, or Accomodations	10.02	9.26	4.68	6.20	8.59	8.49	8.38	8.36
Other Services	4.45	4.67	4.93	4.34	4.77	4.92	4.75	4.84
Public Administration	7.87	5.92	6.62	6.39	7.42	5.50	7.39	5.62
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Total Employed Persons	64,176	73,394	57,434	65,325	512,369	598,018	633,978	736,737
Labor Force Participation (% of the Population at Least 16 years old)								
In the labor force	49.76	50.36	66.95	68.81	59.52	64.31	58.81	62.83
Not in the labor force	50.24	49.64	33.05	31.19	40.48	35.69	41.19	37.17
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Population at least 16 years old	155,633	169,051	90,169	101,959	948,538	1,013,512	1,194,340	1,284,522
Unemployment (% of the labor force unemployed)								
Unemployed	9.44	6.94	4.16	4.55	5.91	5.26	6.24	5.43
Employed	90.56	93.06	95.84	95.45	94.09	94.74	93.76	94.57
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Population, 16 and up, in the labor force	77,443	85,134	60,368	70,158	564,570	651,790	702,391	807,065
Usual Hours Worked (% of the population, 25-54)								
Employed Part-Time**	21.03	26.26	22.36	22.16	23.80	23.23	23.31	23.50
Employed Full-Time**	34.20	40.91	60.20	67.38	51.56	59.88	49.90	58.28
Not Employed**	44.77	32.83	17.44	10.46	24.64	16.89	26.79	18.22
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Persons, Age 25-54 **	87,717	79,432	51,835	54,580	510,081	549,285	649,633	683,297
Commute to work (% of commuters)								
Commute is over 1 hour	20.29	16.57	10.43	12.42	11.35	13.03	12.17	13.34
Commute is less than 1 hour	79.71	83.43	89.57	87.58	88.65	86.97	87.83	86.66
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Commuters	59,368	63,572	53,198	51,897	477,924	502,767	590,490	618,236

(Philadelphia, continued)

C. ACS technology, education, and housing stock data

	Distressed		Affluent		Other		Overall	
	2007	2022	2007	2022	2007	2022	2007	2022
Technology Access (% of households)								
With an internet subscription*	49.11	76.39	81.27	91.76	72.43	86.08	70.13	85.33
With no internet access*	45.19	19.72	15.98	6.36	23.34	10.77	25.58	11.53
With a mobile smartphone*	51.93	80.16	73.70	89.69	67.57	86.42	66.04	85.91
With a computer*	49.90	54.64	82.04	84.99	70.92	75.85	69.10	73.95
With at least 1 computing device*	68.53	85.66	88.99	95.31	82.64	92.44	81.33	91.82
Total Households*	76,976	83,077	48,808	55,477	465,496	520,575	591,280	659,129
Education Attainment (% of the population 25 years old and older								
Less than a high school education	37.52	26.71	12.13	4.90	20.44	11.79	21.87	13.10
High school diploma or GED	40.25	40.57	25.42	18.61	37.12	29.91	36.57	30.33
Some college or Associates degree	15.89	22.38	22.14	20.97	20.87	23.27	20.36	22.97
Bachelors degree	5.01	6.77	20.91	27.16	12.88	19.85	12.55	18.80
Masters degree or higher	1.59	3.57	19.42	28.37	8.79	15.18	8.75	14.80
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Population 25 Years Old and Older	123,073	136,981	79,706	89,353	800,565	863,678	1,003,343	1,090,012
Housing Stock data (% of total housing units)								
Vacant units	20.92	14.15	15.44	6.48	13.77	9.39	14.87	9.79
Single-family detatched units	7.63	6.02	16.60	13.92	8.12	7.60	8.75	7.90
Single-family attached units	75.19	63.72	46.37	42.48	57.88	50.74	59.27	51.79
Multi-family units	17.08	15.67	36.81	36.58	33.81	32.02	31.80	30.22
Other-type units (mobile homes, etc.)	0.10	14.59	0.22	7.01	0.19	9.64	0.18	10.08
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Incomplete plumbing	8.21	8.71	1.86	1.54	3.01	2.43	3.61	3.19
Incomplete kitchen	10.55	9.64	1.52	1.12	3.82	2.86	4.54	3.62
Total Housing Units	88,582	96,767	53,720	59,320	515,273	574,543	657,575	730,630

(Philadelphia, continued)

D. ACS housing unit data, owners vs. renters

	Distressed		Affluent		Other		Overall	
	2007	2022	2007	2022	2007	2022	2007	2022
Occupied Housing Unit Data (% of total occupied housing units)								
Percent of occupied housing units that are owner-occupied	54.87	48.35	61.11	56.15	58.89	52.41	58.57	52.21
Percent of occupied housing units that are renter-occupied	45.13	51.65	38.89	43.85	41.11	47.59	41.43	47.79
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Total Occupied Housing Units	70,053	83,077	45,430	55,477	444,584	520,575	560,067	659,129
Owner-Occupied Housing Unit Data (% of total owner-occupied housing units)								
Valued < $150,000	95.29	74.26	30.54	9.24	55.30	27.72	57.92	31.48
Valued $150,000 - $200,000	1.55	9.91	19.75	8.50	16.56	15.35	15.06	14.10
Valued $200,000 - $300,000	1.91	10.17	27.85	30.82	15.80	27.41	15.19	25.70
Valued $300,000 - $400,000	0.76	2.51	11.17	25.16	6.24	12.49	6.01	12.47
Valued $400,000 - $500,000	0.17	0.84	5.08	11.00	2.73	6.22	2.63	6.03
Valued $500,000 and Over	0.32	2.31	5.62	15.29	3.36	10.80	3.19	10.22
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Total Owner-Occupied Housing Units	38,978	40,167	27,967	31,152	264,038	272,830	330,983	344,149
Renter-Occupied Housing Unit Data (% of total owner-occupied housing units)								
Percent of renter households that are burdened (30% of more of their monthly income spent on rent)	56.67	58.47	47.25	40.28	48.28	47.62	49.34	48.53
Percent of renter households that are extremely burdened (50% of more of their monthly income spent on rent)	37.29	37.80	29.11	20.29	26.98	26.06	28.55	27.21
Total Renter-Occupied Housing Units	31,614	42,910	17,709	24,325	182,777	247,745	232,100	314,980

(Philadelphia, continued)

E. HMDA data on loan applications, denials, and originations

HOME MORTGAGE DISCLOSURE ACT (HMDA)	Distressed		Affluent		Other		Overall	
	2007	2022	2007	2022	2007	2022	2007	2022
Total Home-Purchase Loan Applications (% of completed home-purchase loan applications)								
Originated	56.99	78.16	79.96	92.69	71.35	87.20	70.92	87.03
Denied	32.71	18.61	12.90	5.69	19.07	10.04	19.66	10.28
Approved, but not accepted	10.30	3.23	7.14	1.62	9.58	2.76	9.42	2.69
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Total Home-Purchase Loan Applications	1,932	1,209	2,046	1,546	19,455	12,261	23,433	15,016
Total Home-Purchase Loan Applications for Loans Under $150k (% of completed home-purchase loan applications for loans under $150k)								
Originated	57.70	76.03	76.39	80.95	68.97	76.08	67.86	76.24
Denied	31.86	21.21	14.79	14.29	21.54	19.65	22.56	19.84
Approved, but not accepted	10.44	2.76	8.82	4.76	9.49	4.27	9.58	3.92
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Total Home-Purchase Loan Applications, Under $150k	1,877	580	703	84	11,790	1,710	14,370	2,374
	Distressed		Affluent		Other		Overall	
	2007	2022	2007	2022	2007	2022	2007	2022
Total Home-Purchase Loan Applications for Loans $150k and Over (% of completed home-purchase loan applications for loans $150k and over)								
Originated	32.73	80.13	81.83	93.37	75.00	89.00	75.56	89.06
Denied	61.82	16.22	11.91	5.20	15.28	8.48	15.06	8.49
Approved, but not accepted	5.45	3.65	6.26	1.43	9.72	2.52	9.38	2.45
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Total Home-Purchase Loan Applications, $150k and Over	55	629	1,343	1,462	7,665	10,551	9,063	12,642
Total Originated Home-Purchase Loans (% of originated completed home-purchase loan applications)								
Less than $150,000	98.37	46.67	32.82	4.75	58.58	12.17	58.68	13.85
$150,000 to $200,000	1.18	21.16	27.69	6.14	16.73	16.86	16.78	15.99
$200,000 to $250,000	0.36	12.49	18.64	14.17	9.20	19.10	9.54	18.08
$250,000 to $300,000	0.09	5.08	9.84	21.56	5.04	16.33	5.18	16.09
$300,000 to $350,000	0.00	3.60	5.62	17.45	3.32	9.91	3.33	10.28
$350,000 to $400,000	0.00	4.34	2.14	12.35	2.38	6.38	2.20	6.89
$400,000 to $450,000	0.00	2.43	1.28	6.28	2.35	4.76	2.09	4.76
$450,000 to $500,000	0.00	2.01	0.18	4.61	0.35	3.54	0.31	3.54
$500,00 and Over	0.00	2.22	1.77	12.70	2.05	10.96	1.88	10.52
Missing	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Total Originated Home-Purchase Loans	1,101	945	1,636	1,433	13,881	10,691	16,618	13,069
Total Home-Improvement Loan Applications (% of completed home-improvement loan applications)								
Originated	25.40	32.11	53.75	63.04	37.99	45.44	36.42	43.99
Denied	67.45	65.93	36.95	35.51	52.08	52.52	54.24	54.03
Approved, but not accepted	7.15	1.96	9.30	1.45	9.93	2.04	9.34	1.98
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Total Home-Improvement Loan Applications	1,315	408	387	138	4,956	1,525	6,658	2,071

(Philadelphia, continued)

F. CoreLogic data on housing sales and prices

CORELOGIC data	Distressed		Affluent		Other		Overall	
	2007	2022	2007	2022	2007	2022	2007	2022
Housing Affordability								
Fair Market Price for the Average Home ($)	64,180	127,448	261,216	389,624	178,589	296,711	174,690	286,936
Percentage change, 2007-2020		*98.6%*		*49.2%*		*66.1%*		*64.3%*
Per capita income (ACS data)	$10,940	$18,489	$32,637	$53,139	$20,763	$36,896	$20,181	$35,552
Percentage change, 2007-2020		*69.0%*		*62.8%*		*77.7%*		*76.2%*
Yrs. to Purchase Home (Avg. area price/per cap. income)	5.87	6.89	8.00	7.33	8.60	8.04	8.66	8.07
Percentage change, 2007-2020		*17.5%*		*-8.4%*		*-6.5%*		*-6.8%*
Fair Market Price Per Square foot ($)	49.28	100.12	162.31	233.40	137.63	225.04	132.10	214.12
Percentage change, 2007-2020		*103.2%*		*43.8%*		*63.5%*		*62.1%*
Homes Bought/Sold (% of all homes bought/sold)								
Less than $200,000	98.76	87.39	36.15	12.11	74.23	37.97	73.24	41.38
$200,000 to $250,000	0.23	4.68	27.45	11.31	9.41	14.81	10.12	13.38
$250,000 to $300,000	0.17	3.04	14.20	15.88	4.92	14.21	5.28	13.10
$300,000 to $350,000	0.62	1.35	8.69	16.96	3.47	9.31	3.66	9.05
$350,000 to $400,000	0.00	0.93	5.07	13.76	2.17	5.80	2.22	5.91
$400,000 to $450,000	0.06	0.46	2.25	7.42	1.32	3.92	1.28	3.82
$450,000 to $500,000	0.00	0.46	1.06	4.45	1.01	2.63	0.91	2.54
$500,000 and Over	0.11	1.60	5.13	18.05	3.46	11.34	3.27	10.80
Missing Sale Amount ($) Information	0.06	0.08	0.00	0.06	0.01	0.01	0.02	0.02
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Bought with cash	22.74	49.01	9.94	19.65	14.67	29.99	15.06	31.27
Bought with mortgage	77.26	50.99	90.06	80.35	85.31	70.01	84.93	68.73
Unknown	0.00	0.00	0.00	0.00	0.02	0.01	0.02	0.00
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Bought by a business	17.83	45.17	4.07	11.76	7.94	20.67	8.59	22.69
Bought by a non-business (Person, or couple)	82.17	54.83	95.93	88.24	92.06	79.33	91.41	77.31
Unknown	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Buyer will not occupy	40.74	60.14	17.57	25.47	24.42	40.95	25.45	41.82
Buyer will occupy	56.04	38.00	81.30	73.84	73.81	58.07	72.70	57.12
Unknown	3.33	1.94	1.13	0.74	1.93	1.11	2.00	1.17
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Total Homes Bought/Sold	1,772	2,371	1,599	1,751	14,191	16,954	17,562	21,076

(Philadelphia, continued)

	Distressed		Affluent		Other		Overall	
	2007	2022	2007	2022	2007	2022	2007	2022
Homes Bought by a Business (% of all homes bought by a business)								
Less than $200,000	95.25	93.46	63.08	41.26	85.89	76.41	86.87	78.71
$200,000 and Over	4.75	6.35	36.92	58.25	14.02	23.57	13.06	21.20
Missing Sale Amount ($) Information	0.00	0.19	0.00	0.49	0.09	0.03	0.07	0.08
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Total Homes Bought by Business	316	1,071	65	206	1,127	3,505	1,508	4,782
Homes Bought Without the Intention to Occupy (% of all homes bought without the intention to occupy)								
Less than $200,000	97.78	92.64	56.23	27.13	84.42	56.07	84.81	60.52
$200,000 and Over	2.08	7.36	43.77	72.87	15.58	43.91	15.17	39.47
Missing Sale Amount ($) Information	0.14	0.00	0.00	0.00	0.00	0.01	0.02	0.01
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
›tal Homes Bought Without the Intention to Occupy	722	1,426	281	446	3,466	6,943	4,469	8,815
Homes with Cash (% of all homes bought with cash)								
Less than $200,000	97.27	96.04	59.75	33.14	83.19	62.12	83.93	66.59
$200,000 and Over	2.73	3.06	40.25	0.77	16.81	37.88	16.07	33.41
Missing Sale Amount ($) Information	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Total Homes Bought With Cash	403	1,162	159	344	2,082	5,084	2,644	6,590

NOTES

* These variables only have available data for years after 2016. So, in the columns for **2007**, for these variables, the year measured is 2017.

** These variables only have available data for years after 2013. So, in the columns for **2007**, for these variables, the year measured is 2014.

For ACS data, excluding the technology and hours-worked variables, the 2007 estimates were linearly extrapolated back from 2009.

Appendix D. St. Louis: Descriptive Statistics

A. ACS demographic, migration, and economic data

ST. LOUIS	Distressed		Affluent		Other		Overall	
	2007	2022	2007	2022	2007	2022	2007	2022
AMERICAN COMMUNITY SURVEY (ACS) 5-YEAR ESTIMATES								
Demographic data (% of total population)								
Non-Hispanic Black	93.30	92.39	29.19	27.01	31.39	39.70	48.02	43.70
Non-Hispanic White	4.39	4.26	64.34	60.18	56.74	42.55	45.70	44.61
Non-Hispanic Asian	0.21	0.05	1.65	4.72	5.22	3.53	1.90	3.47
Non-Hispanic Other	1.58	2.47	1.56	3.94	2.38	5.48	1.72	3.92
Hispanic	0.52	0.83	3.25	4.15	4.27	8.74	2.65	4.31
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Less than 18 years old	26.33	23.17	21.59	14.93	27.43	24.30	24.04	18.52
19-25 years old	9.89	7.64	8.69	9.88	7.39	8.50	8.79	9.13
25-65 years old	49.48	50.62	58.65	60.90	55.18	56.86	55.37	57.89
65+ years old	14.32	18.57	11.11	14.30	9.99	10.34	11.83	14.47
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Male	44.44	46.62	48.45	49.16	46.59	49.24	46.95	48.62
Female	55.56	53.38	51.55	50.84	53.41	50.76	53.05	51.38
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Total Population	107,232	64,998	196,616	175,911	69,292	57,109	373,140	298,018
Migration (% of the population, at least 1 year old)								
Lived in the same house 1 year ago	77.81	86.88	80.26	82.57	81.26	86.75	79.73	84.31
Lived elsewhere 1 year ago	6.66	5.61	8.50	9.22	5.17	5.17	7.36	7.66
Lived outside of the U.S. 1 year ago	0.12	0.10	0.81	0.73	1.04	0.19	0.65	0.49
Population at least 1 year old	105,917	64,197	192,933	173,716	66,542	56,181	365,392	294,094
Economic data								
Income per capita ($)	13,212	21,045	25,003	45,744	15,576	26,775	19,864	36,722
Percent of households below the federal poverty line	31.43	31.55	15.34	15.60	25.58	23.38	20.97	20.05
Percent of households on SNAP/food stamps	31.20	34.67	10.43	10.56	19.54	27.79	16.95	18.26
Percent with at least 1 vehicle	71.50	69.40	82.88	86.05	78.33	78.50	79.39	81.51
Total Households	33,664	27,493	84,101	90,133	26,478	25,433	144,242	143,059

(St. Louis, continued)

B. ACS industry and labor force data

	Distressed		Affluent		Other		Overall	
	2007	2022	2007	2022	2007	2022	2007	2022
Industry of Employment (% of employed people)								
Agriculture, Forestry, Fishing, Hunting, or Mining	0.78	0.56	0.26	0.38	0.23	0.36	0.37	0.40
Construction	4.22	4.74	5.19	3.38	6.01	4.64	5.12	3.82
Manufacturing	8.23	9.09	8.86	8.36	12.21	8.38	9.31	8.48
Wholesale Trade	1.64	2.43	2.72	2.17	3.94	1.53	2.70	2.09
Retail Trade	9.67	10.20	10.48	7.24	12.62	13.30	10.68	8.80
Transportation, Warehousing, or Utilities	6.71	8.06	4.36	4.52	4.15	6.10	4.83	5.36
Information	2.77	1.34	3.55	2.15	1.12	1.12	2.96	1.84
Finance, Insurance, or Real Estate	5.29	5.39	7.12	8.15	4.68	5.77	6.30	7.29
Professional, Scientific, Waste Management, or Administration	7.73	7.72	11.93	13.94	9.68	9.69	10.63	12.19
Education Services, Healthcare, or Social Services	28.58	29.24	24.74	30.14	23.33	23.87	25.33	28.87
Arts, Entertainment, Recreation, or Accomodations	11.21	10.96	10.87	10.46	11.29	16.07	11.02	11.55
Other Services	6.09	5.31	5.11	4.91	4.70	5.50	5.25	5.08
Public Administration	7.08	4.96	4.80	4.20	6.03	3.65	5.51	4.22
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Total Employed Persons	36,472	24,493	102,573	102,250	29,402	27,946	168,447	154,689
Labor Force Participation (% of the Population at Least 16 years old)								
In the labor force	55.06	53.82	69.35	70.08	63.64	67.25	64.29	66.21
Not in the labor force	44.94	46.18	30.65	29.92	36.36	32.75	35.71	33.79
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Population at least 16 years old	83,102	51,309	158,270	152,032	51,671	44,885	293,042	248,226
Unemployment (% of the labor force unemployed)								
Unemployed	11.88	6.01	5.20	2.39	7.17	4.77	7.44	3.57
Employed	88.12	93.99	94.80	97.61	92.83	95.23	92.56	96.43
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Population, 16 and up, in the labor force	45,756	27,615	109,760	106,544	32,883	30,185	188,397	164,350
Usual Hours Worked (% of the population, 25-54)								
Employed Part-Time**	27.55	26.33	23.86	19.00	26.52	25.08	25.14	21.42
Employed Full-Time**	35.37	47.67	60.55	69.93	48.78	58.32	53.10	63.88
Not Employed**	37.08	26.00	15.59	11.07	24.70	16.60	21.76	14.70
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Persons, Age 25-54**	29,265	23,419	85,962	85,709	28,039	25,096	143,266	134,224
Commute to work (% of commuters)								
Commute is over 1 hour	11.08	9.38	3.79	3.18	8.07	5.32	6.12	4.59
Commute is less than 1 hour	88.92	90.62	96.21	96.82	91.93	94.68	93.88	95.41
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Commuters	34,105	22,003	96,302	86,808	28,502	23,964	158,909	132,775

(St. Louis, continued)

C. ACS technology, education, and housing stock data

	Distressed		Affluent		Other		Overall	
	2007	2022	2007	2022	2007	2022	2007	2022
Technology Access (% of households)								
With an internet subscription*	45.40	69.27	76.99	88.04	63.31	80.64	68.08	83.12
With no internet access*	46.82	27.39	18.51	9.12	30.86	16.75	26.52	13.99
With a mobile smartphone*	53.55	73.11	73.43	88.74	60.38	81.68	67.03	84.48
With a computer*	45.77	45.70	77.10	79.26	58.71	62.79	67.41	69.88
With at least 1 computing device*	67.50	79.57	86.47	93.64	75.24	87.94	80.58	89.92
Total Households*	28,811	27,493	86,379	90,133	24,551	25,433	139,741	143,059
Education Attainment (% of the population 25 years old and older								
Less than a high school education	31.63	17.50	15.91	6.14	25.64	14.66	21.95	10.02
High school diploma or GED	33.03	38.07	24.39	17.44	34.32	33.93	28.54	24.68
Some college or Associates degree	25.42	31.52	26.12	24.37	24.92	28.98	25.71	26.68
Bachelors degree	7.57	8.30	18.64	28.23	9.95	13.70	14.05	21.49
Masters degree or higher	2.47	4.61	15.00	23.82	5.21	8.73	9.82	17.13
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Population 25 Years Old and Older	68,422	44,970	137,169	132,280	45,160	38,382	250,751	215,632
Housing Stock data (% of total housing units)								
Vacant units	28.22	32.40	18.16	11.80	20.64	17.79	21.19	17.68
Single-family detached units	48.94	36.79	41.56	36.08	45.89	42.98	44.24	37.48
Single-family attached units	4.82	2.70	3.94	4.29	2.11	1.49	3.83	3.42
Multi-family units	46.08	27.84	54.23	47.64	52.07	37.07	51.74	41.12
Other-type units (mobile homes, etc.)	0.16	32.67	0.28	11.99	0.00	18.47	0.18	17.98
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Incomplete plumbing	8.25	14.87	1.52	1.69	1.34	3.00	3.21	5.01
Incomplete kitchen	12.96	21.95	3.05	3.32	4.29	5.89	5.82	8.14
Total Housing Units	46,897	40,670	102,677	102,186	33,366	30,936	182,939	173,792

(St. Louis, continued)

D. ACS housing unit data, owners vs. renters

	Distressed		Affluent		Other		Overall	
	2007	2022	2007	2022	2007	2022	2007	2022
Occupied Housing Unit Data (% of total occupied housing units)								
Percent of occupied housing units that are owner-occupied	50.15	43.69	52.15	46.06	53.38	41.87	51.91	44.86
Percent of occupied housing units that are renter-occupied	49.85	56.31	47.85	53.94	46.62	58.13	48.09	55.14
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Total Occupied Housing Units	33,664	27,493	84,101	90,133	26,478	25,433	144,242	143,059
Owner-Occupied Housing Unit Data (% of total owner-occupied housing units)								
Valued < $150,000	91.41	83.92	46.33	21.81	83.80	71.02	63.59	41.60
Valued $150,000 - $200,000	4.77	6.68	24.87	19.54	9.37	13.63	17.40	16.15
Valued $200,000 - $300,000	2.69	4.22	16.22	28.93	4.31	7.55	10.92	20.75
Valued $300,000 - $400,000	0.54	1.30	6.80	16.05	1.53	3.07	4.39	11.13
Valued $400,000 - $500,000	0.04	0.46	2.21	6.24	0.68	2.31	1.43	4.51
Valued $500,000 and Over	0.55	3.41	3.57	7.43	0.31	2.42	2.27	5.85
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Total Owner-Occupied Housing Units	17,056	12,012	44,141	41,513	14,216	10,648	75,413	64,173
Renter-Occupied Housing Unit Data (% of total owner-occupied housing units)								
Percent of renter households that are burdened (30% of more of their monthly income spent on rent)	54.44	51.54	41.10	39.72	52.54	47.35	46.36	43.47
Percent of renter households that are extremely burdened (50% of more of their monthly income spent on rent)	32.51	31.39	21.49	21.01	32.93	25.98	26.19	23.98
Total Renter-Occupied Housing Units	16,782	15,481	40,254	48,620	12,343	14,785	69,379	78,886

(St. Louis, continued)

E. HMDA data on loan applications, denials, and originations

HOME MORTGAGE DISCLOSURE ACT (HMDA)	Distressed		Affluent		Other		Overall	
	2007	2022	2007	2022	2007	2022	2007	2022
Total Home-Purchase Loan Applications (% of completed home-purchase loan applications)								
Originated	43.03	66.29	74.83	91.00	57.39	86.55	65.90	88.93
Denied	44.48	29.21	15.09	5.89	32.68	9.65	23.63	7.76
Approved, but not accepted	12.49	4.50	10.08	3.11	9.93	3.80	10.47	3.31
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Total Home-Purchase Loan Applications	1,169	178	4,208	2,732	1,279	684	6,656	3,594
Total Home-Purchase Loan Applications for Loans Under $150k (% of completed home-purchase loan applications for loans under $150k)								
Originated	43.84	63.83	75.58	86.49	58.86	83.86	63.78	82.15
Denied	44.66	31.21	14.13	9.59	31.34	12.97	25.52	14.04
Approved, but not accepted	11.50	4.96	10.29	3.92	9.80	3.17	10.70	3.81
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Total Home-Purchase Loan Applications, Under $150k	1,104	141	2,428	459	1,123	347	4,655	947

	Distressed		Affluent		Other		Overall	
	2007	2022	2007	2022	2007	2022	2007	2022
Total Home-Purchase Loan Applications for Loans $150k and Over (% of completed home-purchase loan applications for loans $150k and over)								
Originated	46.15	75.68	73.82	91.90	46.79	89.32	70.81	91.35
Denied	41.54	21.62	16.40	5.15	42.31	6.23	19.24	5.52
Approved, but not accepted	12.31	2.70	9.78	2.95	10.90	4.45	9.95	3.13
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Total Home-Purchase Loan Applications, $150k and Over	65	37	1,780	2,273	156	337	2,001	2,647
Total Originated Home-Purchase Loans (% of originated completed home-purchase loan applications)								
Less than $150,000	94.04	76.27	58.27	15.97	90.05	49.16	67.69	24.34
$150,000 to $200,000	3.18	16.10	21.02	23.37	6.81	27.03	16.60	23.78
$200,000 to $250,000	2.78	6.78	10.64	19.03	1.91	8.95	8.28	16.71
$250,000 to $300,000	0.00	0.85	4.29	12.95	0.82	6.25	3.21	11.26
$300,000 to $350,000	0.00	0.00	2.22	10.58	0.14	4.22	1.62	9.01
$350,000 to $400,000	0.00	0.00	1.27	6.64	0.27	2.03	0.96	5.54
$400,000 to $450,000	0.00	0.00	0.89	3.70	0.00	0.84	0.64	3.04
$450,000 to $500,000	0.00	0.00	0.16	2.29	0.00	0.51	0.11	1.88
$500,00 and Over	0.00	0.00	1.24	5.47	0.00	1.01	0.89	4.44
Missing	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Total Originated Home-Purchase Loans	503	118	3,149	2,486	734	592	4,386	3,196
Total Home-Improvement Loan Applications (% of completed home-improvement loan applications)								
Originated	24.45	12.37	39.74	57.73	27.54	36.36	31.44	35.19
Denied	66.76	84.54	51.43	38.14	61.08	63.64	59.28	61.57
Approved, but not accepted	8.79	3.09	8.83	4.13	11.38	0.00	9.28	3.24
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Total Home-Improvement Loan Applications	89	12	385	97	167	22	288	76

F. CoreLogic data on housing sales and prices

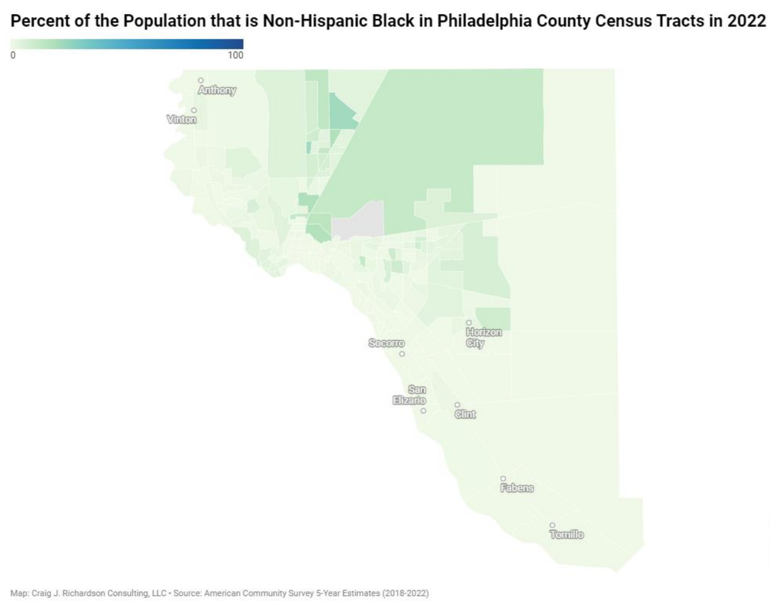
	Distressed		Affluent		Other		Overall	
CORELOGIC	2007	2022	2007	2022	2007	2022	2007	2022
Housing Affordability								
Fair Market Price for the Average Home ($)	54,655	52,441	163,754	247,320	92,777	133,606	126,800	192,982
Percentage change, 2007-2020		*-4.1%*		*51.0%*		*44.0%*		*52.2%*
Per capita income (ACS data)	$13,212	$21,045	$25,003	$45,744	$15,576	$26,775	$19,864	$36,722
Percentage change, 2007-2020		*59.3%*		*83.0%*		*71.9%*		*84.9%*
Yrs. to Purchase Home (Avg. area price/per cap. income)	4.14	2.49	6.55	5.41	5.96	4.99	6.38	5.26
Percentage change, 2007-2020		*-39.8%*		*-17.4%*		*-16.2%*		*-17.7%*
Fair Market Price Per Square foot ($)	33.74	34.25	109.31	165.10	65.60	93.22	85.81	129.67
Percentage change, 2007-2020		*1.5%*		*51.0%*		*42.1%*		*51.1%*
Homes Bought/Sold (% of all homes bought/sold)								
Less than $200,000	45.46	63.32	47.27	37.82	56.97	66.89	48.82	49.13
$200,000 to $250,000	0.28	0.41	6.20	14.09	0.89	5.58	3.59	9.61
$250,000 to $300,000	0.11	0.14	3.31	10.62	0.34	2.68	1.88	6.87
$300,000 to $350,000	0.06	0.14	1.56	7.55	0.21	2.11	0.90	4.94
$350,000 to $400,000	0.00	0.00	0.95	5.51	0.00	1.03	0.51	3.47
$400,000 to $450,000	0.00	0.07	0.85	3.68	0.14	0.40	0.48	2.27
$450,000 to $500,000	0.00	0.00	0.24	2.02	0.07	0.40	0.14	1.28
$500,000 and Over	0.00	0.55	1.30	6.40	0.13	1.14	0.73	4.12
Missing Sale Amount ($) Information	54.09	35.38	38.31	12.30	41.25	19.77	42.95	18.31
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Bought with cash	53.87	78.41	28.58	30.66	36.17	45.47	36.62	42.93
Bought with mortgage	45.85	21.11	71.29	69.32	63.62	54.53	63.19	56.97
Unknown	0.28	0.48	0.13	0.02	0.21	0.00	0.19	0.10
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Bought by a business	29.66	50.07	20.52	26.95	29.99	44.73	24.82	35.28
Bought by a non-business (Person, or couple)	70.34	49.93	79.48	73.05	70.01	55.27	75.18	64.72
Unknown	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Buyer will not occupy	54.92	77.25	33.38	38.28	45.57	54.81	41.42	49.30
Buyer will occupy	40.12	18.72	65.01	59.70	51.68	40.11	55.88	47.62
Unknown	4.95	4.03	1.64	2.02	2.75	5.07	2.72	3.08
TOTAL	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Total Homes Bought/Sold	1,797	1,464	3,772	4,593	1,457	1,755	7,026	7,812

(St. Louis, continued)

Appendix E. Racial Composition, Per Capita Income, and Mortgage Denial Rates

These maps serve to give an overview along the lines of racial composition, income per capita, and denial rates of loan applications. St. Louis is the most strongly divided along these lines, with the highest degree of racial segregation. The northern area of St. Louis has high percentages of Black residents, along with some of the lowest per capita incomes and markedly higher mortgage denial rates. The other cities have a less obvious connection among the three variables.

A. Percentage of the Population that is Non-Hispanic Black



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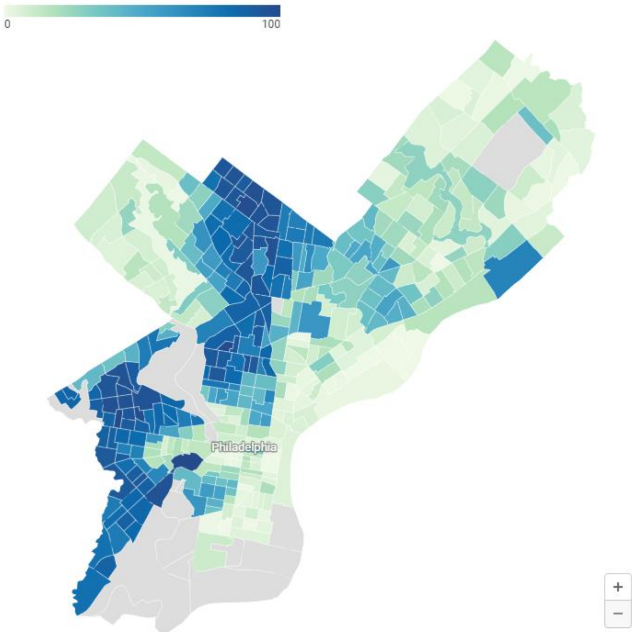
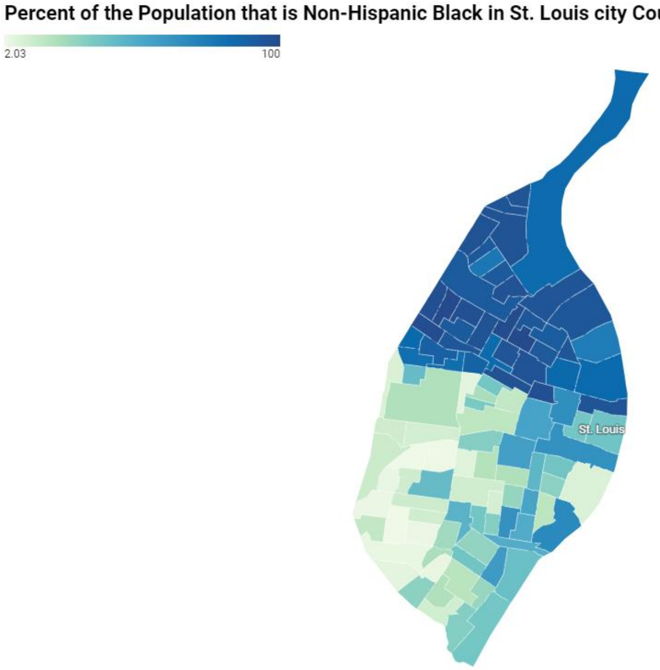
Percent of the Population that is Non-Hispanic Black in Philadelphia County Census Tracts in 2022



Map: Craig J. Richardson Consulting, LLC • Source: American Community Survey (ACS) 2022 5-Year Estimates • Get the data

https://datawrapper.dwcdn.net/a8zu6/2/

Percent of the Population that is Non-Hispanic Black in St. Louis city County Census Tracts in 2022



Map: Craig J. Richardson Consulting, LLC • Source: American Community Survey (ACS) 5-Year Estimates 2018-2022 • Get the data

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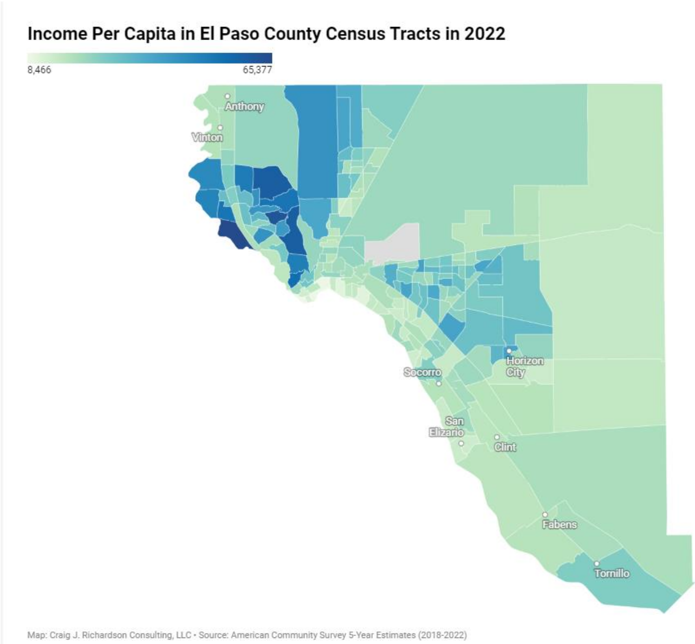
B. Income Per Capita, 2022



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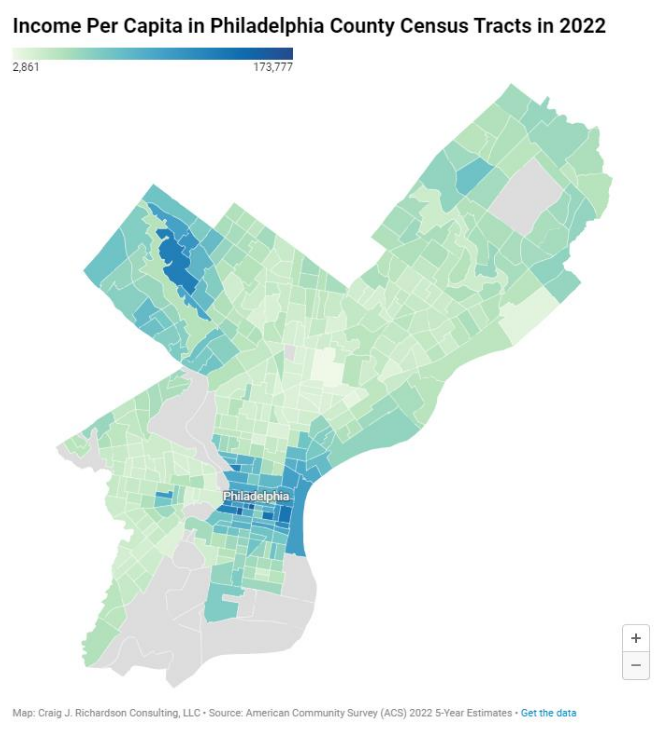

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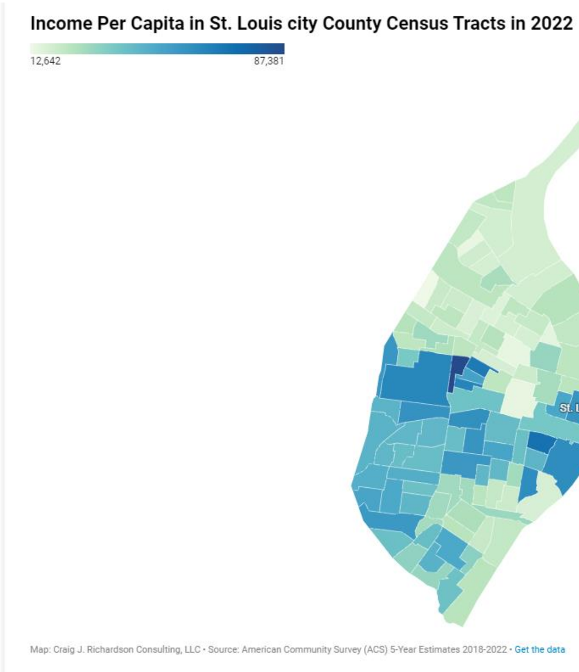

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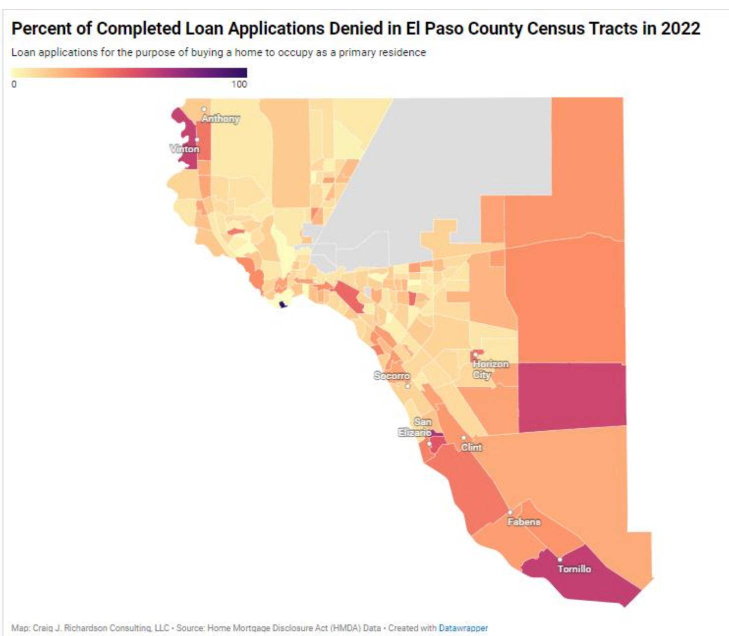
C. Percentage of completed loan applications denied in 2022



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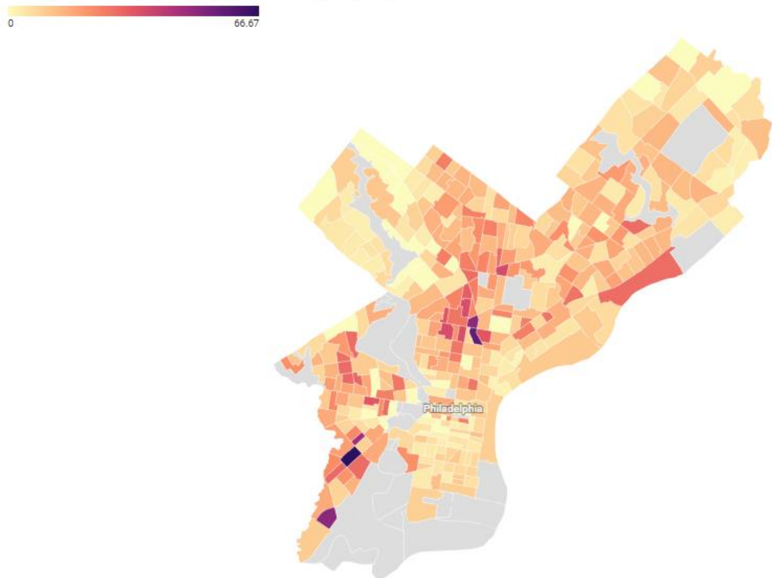
Percent of Completed Loan Applications Denied in Philadelphia County Census Tracts in 2022

Loan applications for the purpose of buying a home to occupy as a primary residence



Map: Craig J. Richardson Consulting, LLC • Source: Home Mortgage Disclosure Act (HMDA) Data • Get the data • Created with Datawrapper

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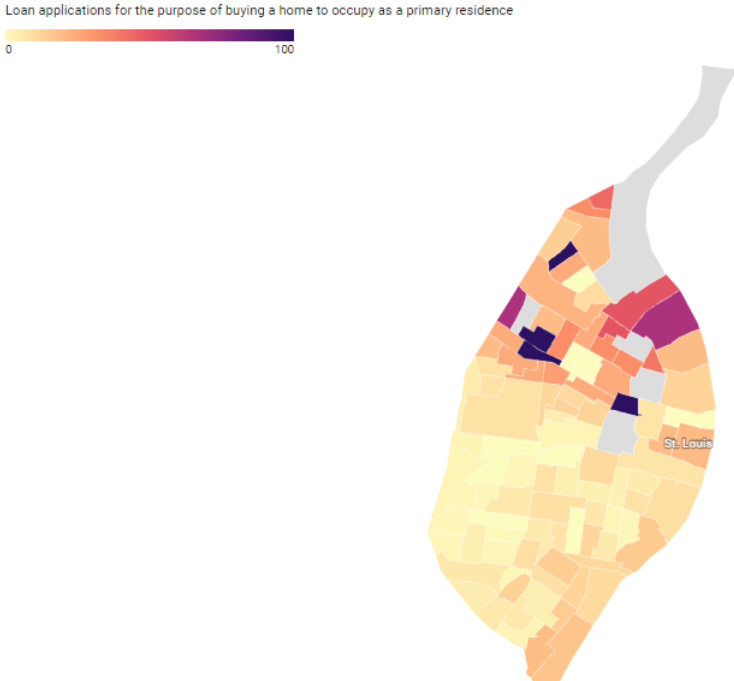
Percent of Completed Loan Applications Denied in St. Louis Census Tracts in 2022

Loan applications for the purpose of buying a home to occupy as a primary residence



Map: Craig J. Richardson Consulting, LLC • Source: Home Mortgage Disclosure Act (HMDA) Data • Get the data • Created with Datawrapper

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END OF REPORT