2019

Making Room for Quantitative Literacy in Historic Preservation: Local Historic District Designation and Property Values as a Case Study

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Making Room for Quantitative Literacy in Historic Preservation: Local Historic District Designation and Property Values as a Case Study

Abstract
This thesis calls for a twofold shift in the training in and practice of historic preservation: first, increased data literacy and use of data in the discipline, and second, for a higher degree of skepticism about the implications of data-driven findings. Even if the results of quantitative studies are less definitive in their findings than preservation advocates would like, these grey areas can serve a valuable purpose of forcing stakeholders to become more deeply engaged in why effects might be what they are, and how policy can intervene to achieve more desirable outcomes. Following a review of previous studies and their methodologies, this project looks to Philadelphia as a case study for the quantitative analysis of the association between local historic district designation and residential property values, exploring whether it is possible to develop a straightforward and meaningful methodology for assessing the economic impact of local historic district designation on residential property values. Transaction prices serve as the dependent variable in three separate models, each corresponding to a locally designated historic district and a similar but undesignated neighborhood. Limitations are explored in detail, and future directions for study are outlined in order to offer insight to others who might undertake similar work going forward.

Keywords
Economic impact, Statistics, GIS, data management, income-generating property

Disciplines
Economics | Historic Preservation and Conservation

Comments
Suggested Citation:
MAKING ROOM FOR QUANTITATIVE LITERACY IN HISTORIC PRESERVATION:

LOCAL HISTORIC DISTRICT DESIGNATION AND PROPERTY VALUES AS A CASE STUDY

Julia Salas Cohen

A THESIS

in

Historic Preservation

Presented to the Faculties of the University of Pennsylvania in Partial Fulfillment of the Requirements of the Degree of

MASTER OF SCIENCE IN HISTORIC PRESERVATION

2019

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ACKNOWLEDGEMENTS

Immense gratitude goes to David Hollenberg, whose thoughtful guidance helped me settle on this project after many turns along the way. Thank you for supporting me when there wasn’t always an end in sight. Thanks also to Donovan Rypkema, whose course sparked my interest in this topic, and who offered key feedback on drafts of this thesis.

Finally, thank you to the many strong women who have supported me over the past three years. I am honored to have gone through this with all of you.
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INTRODUCTION

As Jennifer Most writes in “The Case for Data Analytics in Preservation Education and Practice,” preservationists produce quantitative studies “largely in a reactive way, defending themselves against specific claims or defending the field more broadly.”¹ Because so much preservation work is reactive, and because methodological approaches are often glossed over in favor of accessibility, existing quantitatively-oriented preservation studies remain open to criticism and potential refutation. Academic historic preservation programs have been slow to establish data analysis as a core skill, alongside more typically taught methods like historical research, architectural survey, or building recording techniques.² In fact, a study that Most conducted on the inclusion of data and spatial analysis courses within historic preservation programs in the U.S. found that only three of the thirty programs surveyed offered such material within a broader course in a historic preservation department during the 2017-2018 academic year, and few others required students to take a course in quantitative methods or spatial analysis taught elsewhere in a university.³

Instead of leaving methodological approaches out of reports to make results more accessible to audiences unfamiliar with quantitative methods, this thesis proposes that the field of historic preservation work toward increased comfort with and transparency around data and quantitative approaches. By following open data trends, in which

² This has begun to change in recent years, as introductory GIS courses (usually taught through other academic departments) have become more commonplace as electives in historic preservation programs.
³ Most, “The Case for Data Analytics,” 70.
datasets (and the code used in quantitative models) are made publicly available to others who may want to modify, verify, or reproduce results, preservationists can support one another’s work and better integrate historic preservation with allied fields. That is not to say that reports can or should sacrifice qualitative approaches and policy discussion in favor of data, but rather that a variety of approaches need to be made available to offer a more complete understanding of preservation policy issues and outcomes. For this to happen, not only must more data be collected, but preservation planners must be able to work with existing and new datasets, and to be able to critically engage with each other and with colleagues in adjacent fields.

Even if the results of quantitative studies are less definitive in their findings than preservation advocates would like, these grey areas can serve a valuable purpose of forcing stakeholders to become more deeply engaged in why certain effects might be what they are, and how policy can intervene to achieve more desirable outcomes. An expectation for historic preservationists working in policy to have a grounding in quantitative methods would allow for deeper engagement with the work being done in adjacent fields. Data analysis can help answer the question of what, so that we can more deeply examine the why, how, and for whom.

This thesis calls for a twofold shift in the training in and practice of historic preservation: first, increased data literacy and use of data in the discipline, and second, for a higher degree of skepticism about the implications of data-driven findings. While these goals may seem at odds with one another, a deeper level of engagement from within the field will set the stage for richer conversations and clearer advocacy goals.
Project Outline

Following a review of previous studies and their methodologies, this project looks to Philadelphia as a case study for the quantitative analysis of the association between local historic district designation and residential property values. Before delving into the quantitative model itself, an overview of Philadelphia’s planning, development, preservation context offers background into conditions specific to the city, which has undergone substantial changes over the past twenty years both in its preservation culture and in more general planning and development trends. This context, which does not factor into the model itself, is necessary for understanding additional influences at play, including the limitations of the quantitative model presented in the subsequent section.

Section 4 of this thesis explores whether it is possible to develop a straightforward and meaningful methodology for assessing the economic impact of local historic district designation on residential property values, using three pairs of neighborhoods in Philadelphia as case studies. Transaction prices serve as the models’ dependent variable, with location within a locally designated historic district as one of many predictors. After results of the models are presented, limitations are explored and future directions for study are outlined in order to offer insight to others who might undertake similar work going forward.

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4 Local historic districts, rather than national districts, were chosen for this analysis because they are less closely associated with the Federal Rehabilitation Tax Credit program than are properties listed individually or as contributing to districts on the National Register of Historic Places. In Certified Local Governments (including Philadelphia), locally designated properties and contributing buildings in locally designated districts are also eligible for the Federal Rehabilitation Tax Credit program, provided that they, like any other property receiving the tax credit, are income-generating. This distinction is one of many factors that complicates the use of quantitative methods to evaluate the impact of local historic district designation, particularly when attempting to generalize beyond a single municipality. The inclusion of only residential properties in the quantitative analysis helps narrow the scope of this project and allows for more of an apples to apples comparison than if all types of uses were included.
The final section of this thesis delves into potential policy implications, both of using quantitative models as an evaluation tool in the designation process, and of the potential for increased data literacy among preservation professionals. This portion of the project looks more holistically at economic impact beyond just rising property values, to examine how these effects may impact residents’ quality of life and neighborhood identity and stability, and what role historic preservation might play in ensuring sustained positive outcomes.
PREVIOUS STUDIES

Economic impact studies of historic preservation often point to a “preservation premium,” claiming that historic districts are associated with higher property values than comparable neighborhoods. These studies allude to quantitative approaches but generally do not delve deeply into their methodologies. They typically highlight rising property values as an unequivocally positive outcome, without exploring how changes in property values within a historic district might impact residents within these areas or in other parts of the city.

These reports, often conducted as part of broader studies commissioned by national, state, and local historic preservation advocacy organizations, frequently gloss over their methodological approaches in favor of simplicity and the strength of the narrative. This thesis explores property values and local historic district designation as a case study into how greater nuance and increased transparency around methodological approaches and quantitative findings could be introduced into preservation planning and policy.

In the introduction to *Preservation and the New Data Landscape*, Erica Avrami frames the need for continued, rigorous study of the impacts that preservation can have on neighborhoods and communities:

Because preservation is often at odds with better financed and politically empowered real estate development interests, studies on the subject are often reactive and geared toward rationalizing investment in heritage by defending the status quo. Despite half a century of local policy experience behind us, there is still much to learn about the positive and negative influence of preservation on the social and physical fabric of cities. A better understanding of that influence can
help policy meet contemporary needs more effectively and serve communities more justly.⁵

In a 2011 report to the Advisory Council on Historic Preservation, *Measuring the Economic Impacts of Historic Preservation*, Donovan Rypkema, Caroline Cheong, and Randall Mason argue for consistent and rigorous data analysis across five major economic measures: jobs and household income, property values, heritage tourism, environmental measurements, and downtown revitalization.

Impact assessments of historic preservation typically also acknowledge other aspects of value that are not purely economic – the recognition of these broader values forms the basis for “values-based preservation,” an approach that considers the social, heritage, environmental, and other values that are associated with a historic site.⁶ Indeed, the benefits of local district designation extend beyond the economic. Although the details of local designation vary greatly among municipalities, benefits can include a strengthened sense of place-based identity among district residents, improved perceptions on the part of other city residents, and the potential for more control by property owners over the built form of their neighborhoods (which can also be a problem, of course). These additional impacts, which are not measured in quantitative economic models, must remain at the center of discussions around historic designation – while a core section of this thesis is centered around statistical modeling, the results are not what matters so much as an understanding that this is a complex issue that cannot be fully captured by a mathematical equation. Nonetheless, the prevalence of quantitative models in discussions around both

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local and national historic district designation (and more broadly, in policy advocacy) makes it worthwhile to delve more deeply into the topic.

Studies that address the association between historic preservation and residential property values typically argue one or more of the following:

- Historic preservation is associated with increased property values.
- Historic preservation is associated with more stable property values.
- Historic preservation is associated with (or causes) gentrification or displacement.
- Historic preservation protects against gentrification or displacement.\(^7\)

In this context (and more generally), historic preservation is defined as the renovation or rehabilitation of formally designated historic structures, whether through the individual designation process or by way of their being identified as contributing buildings in a locally or nationally designated historic district.\(^8\)

Studies that claim that historic designation raises (or is associated with higher) property values generally argue that the prestige and security offered by designation – in the form of a guarantee that a neighborhood will be protected from out-of-scale or out-of-character new development – will offer a “preservation premium.”\(^9\) While statistical approaches can indicate association between designation and property values or transaction prices, claims of causality must be substantiated through policy analysis. On

\(^7\) See page 13 of this thesis for more information on why the dynamic of homeownership and rentership is not typically included explicitly in quantitative models, including in the ones in this document.

\(^8\) Individually-designated buildings (on local, state, or national registers) are generally not studied using this type of quantitative approach, as they represent fewer data points (particularly when exclusively considering occupied residential properties), and they are more likely to represent “exceptional” examples of their type, whether for architectural excellence or by association with a particular individual or historical event.

the other side of this debate, those who find designation to be associated with lower 
property values or prices attribute this to the fact that local designation can restrict 
building uses, thereby preventing a property from realizing its highest and best use, 
particularly in cases where a building’s existing configuration is smaller in scale (or 
otherwise less profitable) than what zoning would allow. Additionally, some point to 
rising prices that may be associated with development restrictions.10

Because local ordinances differ among cities with local historic district 
designations, these districts vary from one city to another. In cities (Philadelphia 
included) where property owners are required to submit plans to the local historical 
commission before performing work on a building’s exterior, critics of historic 
preservation argue that property owners are forced to invest substantially more money 
into renovations than they otherwise might.11

Together, increased renovation costs and higher property values (along with the 
associated increases in property taxes) can contribute to displacement of low- and 
moderate-income residents, including property owners as well as tenants, who might see 
these costs passed on in the form of higher rental rates. While low-income property

10 Vicki Been, et al., “Preserving History or Hindering Growth? The Heterogenous Effects of Historic 
Districts on Local Housing Markets in New York City,” (National Bureau of Economic Research Working 
Paper No. 20446, September 2014), https://www.nber.org/papers/w20446 and Edward Glaeser, 

11 The provision for financial hardship given in the Philadelphia Historical Commission’s Rules and 
Regulations states that a property owner making a claim of financial hardship “must demonstrate that the 
sale of the property is impracticable, that commercial rental cannot provide a reasonable rate of return, and 
that other potential uses of the property are foreclosed. The applicant has an affirmative obligation in good 
faith to attempt the sale of the property, to seek tenants for it, and to explore potential reuses for it.” While 
the owner’s personal finances are not a factor in claims of financial hardship, unnecessary hardship, 
described in Section 11 of Rules and Regulations, exists to mitigate the burden on low- or moderate-income 
households, and includes a confidential review of tax returns. Philadelphia Historical Commission, Rules & 
Regulations, revised February 11, 2010, https://www.phila.gov/media/20190327101224/Historical-
owners can benefit from increased property values if they choose to sell, additional studies are needed to better understand the extent to which these households remain in control of deciding when and if to sell, and where they move once they have sold their properties. Studies concerned with potential displacement or neighborhood-scale gentrification look at household movement, typically using markers of upward or downward moves to identify whether a household was able to take advantage of rising property values to move to a “better” neighborhood (defined by set parameters), or to build wealth.\(^{12}\)

In general, studies evaluating the potential association between historic district designation and property values tend to gloss over the policy implications of whatever relationship is found, instead focusing on quantitative findings that are framed as exclusively positive (or sometimes as exclusively negative). This approach does a disservice to preservation planners and policymakers, who could delve more deeply into precisely who benefits and who loses when property values change. In particular, the dynamic of renters versus homeowners is one that receives less attention than needed, especially when considering the financial incentives associated with the Federal Rehabilitation Tax Credit program, which is reserved for income-generating properties.

**Local Historic District Designation and Property Values**

Because studies of the economic impact of historic district designation treat property values and transaction prices somewhat interchangeably, this thesis will generally refer to

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the association between designation and property values, in line with the language that is more commonly used in the literature. It should be noted, however, that the approach in this thesis uses transaction prices as the dependent variable, not property value.  

In *Measuring the Economic Impacts of Historic Preservation*, Rypkema, Cheong, and Mason advocate for annual evaluation of property values in a representative sample of communities, to establish a consistent approach for measuring the association between local historic districts and property value nationwide. They propose that a national real estate firm could undertake the research, and that property values in the selected communities could be reviewed annually, to establish baseline data over time. This proposal is both ambitious and likely unfeasible, as there is no mechanism for collecting consistent property data across municipalities in the United States. Next steps as given in the report would work toward “Identify[ing] a finite number of indicators that can be used to regularly, consistently, meaningfully, and credibly measure the economic impact of historic preservation over time,” through the following processes:

1. Identify and reach agreement with responsible parties to undertake the ongoing research and data collection for each of the recommended indicators.

2. In conjunction with the responsible parties, create a long-term research, evaluation, and reporting plan.

3. Establish baseline(s) for each of the recommended indicators.

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13 Since the City of Philadelphia instituted the actual value initiative in tax year 2014, assessments are meant to reflect the true market value of properties, although this has not been the case. See pages 30-32 of this thesis for a discussion of Philadelphia’s property assessment.


15 Ibid., 8.
4. Work with the identified parties to systematize data collection.\textsuperscript{16}

Looking more closely at property value as a measure, \textit{Measuring the Economic Impacts of Historic Preservation} addresses the pros and cons of using transaction prices as a proxy for property value. Assessed property values offer a larger sample size than transaction prices (as all properties in a given municipality have an assessed value for tax purposes).\textsuperscript{17} In order to account for variation in residential properties, assessed value per square foot of livable area is given as a possible dependent variable to be used in a model. The use of property assessment as a dependent variable introduces problems of its own, however, as the process can suffer from issues of inconsistency.

An alternative approach using transaction prices can show what actual homebuyers are willing to pay at a given time. \textit{Measuring the Economic Impacts of Historic Preservation} suggests the possibility of looking at changes in individual properties’ sales prices over time (given a sufficiently long study period) to begin to understand whether a property in a local or national historic district might appreciate at a faster or slower rate than a similar property elsewhere in the same city.\textsuperscript{18} \textit{The Economic Benefits of Historic Preservation Activities in Pennsylvania} does just that, using three local historic districts throughout the Commonwealth as case studies.

\textit{Hedonic Regression}

A hedonic regression (or hedonic pricing) approach aims to isolate the effects of individual characteristics (given as predictor variables) on the dependent variable – in this

\textsuperscript{16} Rypkema, Cheong, and Mason, \textit{Measuring the Economic Impacts}, quoted from pages 4-5.
\textsuperscript{17} Ibid., 23.
\textsuperscript{18} Ibid.
case, property value or transaction price. This approach, which is described in greater
detail on pages 43-47 in Section 4 of this thesis, offers the ability to separate various
predictor variables, like the number of bedrooms and bathrooms, building condition, and
presence or absence of a garage, theoretically making it possible to isolate the effect of
historic designation by including that as a variable. This approach is the one used in the
2011 *Economic Benefits of Historic Preservation Activities in Pennsylvania* report and
many others, and it forms the framework for the quantitative approach taken in this thesis.
However, this approach assumes that it is possible to account for all variables that
contribute to property value or transaction price, when limitations in data availability
make this impossible.

In discussing the strengths of hedonic regression, *Measuring the Economic
Impacts of Historic Preservation* argues that because the approach is a well-established
quantitative method, the findings that it offers will minimize potential complaints of bias
compared to approaches that rely solely on surveys or interviews. While past reports by
preservation advocates often only gloss over the quantitative methods that they employ
(generally for the sake of clarity or simplicity), hedonic regression is a familiar and fairly
interpretable technique. In reality, however, there is not always sufficient high-quality data
to build a robust model.

Although there are approximately 580,000 properties within the City of
Philadelphia, and 3.75 million property transactions associated with them over the past
twenty years, data quality issues bring uncertainty into the analysis. Additionally, the use
of a single binary predictor variable – whether a property is located within a local historic

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district or not – removes nuance from conversations about how neighborhoods boundaries are defined and redefined by residents (both owners and renters), developers, realtors, and community organizations.

At the neighborhood scale, different levels of owner occupancy may change the dynamics of what designation means, whether in terms of property values directly, or in how changes may impact residents. This measure is particularly challenging to track in the context of a model, as current occupants are not included in any dataset; the closest proxy for determining owner-occupancy would be through a comparison of the owner mailing address with the property address, and even that has its limitations. Furthermore, as the authors of *Measuring the Economic Impacts of Historic Preservation* acknowledge, inconsistent data collection, together with differences in how property assessments are done across U.S. cities, makes a cross-city comparison impossible using this technique, even within a single state.

Most studies of the association between historic designation and property values use an approach in which transaction values within historic districts in a particular city are compared with those outside of historic districts in the same city. Because these studies generally divide all residential properties with a given city into one of two groups – designated or undesignated (typically, but not exclusively, at the level of local designation) – they do not sufficiently control for other property or neighborhood characteristics.

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20 The records themselves may not be entered consistently, and historic information is not tracked in any publicly available dataset, meaning that all property characteristics apply to a property’s condition at the time of the website OpenDataPhilly’s most recent update for a given dataset.

Some studies look beyond a binary variable to consider proximity to historic districts in addition to simply presence within them. A 2010 report by Econsult Corporation (now Econsult Solutions, Inc.) found a 1.6% increase in residential transaction prices for each mile closer to a national historic district, and a 0.5% for each mile closer to a local historic district.\textsuperscript{22} Given that more than 70 percent of all residential properties in Philadelphia, including all of Center City as well as South, West, and North Philadelphia, are located within two miles of a local historic district (a fact not mentioned in the report itself), this finding should be approached with some degree of skepticism (Figures 1 and 2, on the following page). While this study does separate some neighborhood amenities as additional predictor variables, it does not acknowledge the degree to which these other amenities (like proximity to Center City, transit, or particular schools, for example) may make a difference as well.

While many demographic and neighborhood characteristics can be included as independent variables in a regression model, they depend on data sources that may not be appropriate to the individual building scale. For example, census tracts, used in the neighborhood selection process in this thesis (see Section 4), create artificially defined geographies. Depending on where a property is located within a census tract, this data may be more or less representative of that property’s immediate surroundings. Coulton, Korbin, Chan, and Su address this in their 2001 article “Mapping Residents’ Perceptions of Neighborhood Boundaries: A Methodological Note,” in which they report on a survey

Figure 1: Areas of Philadelphia located within two miles of a local historic district.\textsuperscript{23}

![Map by the author](image)

\textit{Data source: City of Philadelphia}

Figure 2: Properties located within one and two miles of a local historic district.

<table>
<thead>
<tr>
<th>CODE</th>
<th>DESCRIPTION</th>
<th>TOTAL COUNT</th>
<th>WITHIN 1 MILE</th>
<th>WITHIN 2 MILES</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Residential</td>
<td>460,794</td>
<td>44%</td>
<td>71%</td>
</tr>
<tr>
<td>2</td>
<td>Hotels and Apartments</td>
<td>41,685</td>
<td>52%</td>
<td>76%</td>
</tr>
<tr>
<td>3</td>
<td>Stores and Dwellings</td>
<td>14,563</td>
<td>54%</td>
<td>82%</td>
</tr>
<tr>
<td>4</td>
<td>Commercial</td>
<td>13,999</td>
<td>53%</td>
<td>77%</td>
</tr>
<tr>
<td>5</td>
<td>Industrial</td>
<td>4,441</td>
<td>37%</td>
<td>65%</td>
</tr>
<tr>
<td>6</td>
<td>Vacant</td>
<td>44,969</td>
<td>61%</td>
<td>87%</td>
</tr>
<tr>
<td>(SUM)</td>
<td>Total</td>
<td>580,451</td>
<td>46%</td>
<td>73%</td>
</tr>
</tbody>
</table>

\textit{Table by the author}
\textit{Data source: City of Philadelphia}

\textsuperscript{23} Noncontiguous local historic districts (the Historic Street Paving Thematic District and the Ridge Avenue Roxborough Thematic Historic District) are excluded from this analysis.
of Cleveland residents living in seven census block groups. By overlaying neighborhood boundary maps as drawn by residents within each area, the authors highlight areas of overlap and areas of divergence within each neighborhood, with areas identified as within a neighborhood by 70 percent of respondents shaded in. The resulting areas were similar in size to census tracts but did not align with those boundaries, pointing to issues with using census tract data on a neighborhood scale (Figure 3).24 Furthermore, given differing perceptions of neighborhood boundaries among residents, the selection of these boundaries are by nature arbitrary, including in the models given in Section 4 of this thesis (see page 56 for a discussion of boundary selection).

Figure 3: Differing perceptions of neighborhood boundaries in a neighborhood in Cleveland, OH.

Source: Coulton, Korbin, Chan, and Su (2001), 378.

Similarly, differing approaches to measuring the dependent variable can have a substantial impact on how findings are reported. Hanka, et al. explores this in “Contemporary Neighborhood Housing Dynamics in a Mid-Sized US City: The Policy Consequences of Mismeasuring the Dependent Variable,” where neighborhood median values, dollar changes in median values, and percentage changes in median values are all considered as the dependent variable in a model that includes historic district designation, participation in HOPE VI (a federal grant program through the Department of Housing and Urban Development), and the presence of a federally-funded university–community partnership within a given census tract as predictor variables.25 A comparison of eight models found varying associations and levels of significance between each of the three predictor variables described above and whatever dependent variable was used in a given model. While local historic district designation was found to have a positive and significant association with the dependent variables, HOPE VI and university-community partnerships exhibited more complex dynamics that are explored in greater depth in the paper.26

Comparisons Across Municipalities

A 2001 article in Urban Studies by Robin Leichenko, Edward Coulson, and David Listokin broadens the analysis to include a wider sample of properties in several cities, rather than looking at data from an only an individual city. While the authors offer a cogent argument for taking this approach, which fills a clear gap in the literature, this

26 Ibid., 57-60.
broader comparison flattens the substantial differences in both preservation cultures and preservation (and broader planning) ordinances between municipalities, as well as statewide differences. Given the hyper-local nature of historic preservation, particularly in the context of buildings that make up the overall urban fabric (as opposed to landmark buildings), this misses a key part of the discussion.

*The Economic Benefits of Historic Preservation Activities in Pennsylvania*, a 2011 report by Econsult Corporation and Urban Partners, includes three case studies located throughout Pennsylvania (one in Philadelphia, one in West Chester, and one in Pittsburgh) to offer broad insights into how local district designation might reveal different associations with property value or sales prices depending on local context. Each of these three cases evaluates property appreciation before and after designation, relative to either the citywide averages or surrounding neighborhoods.27

Because details about the studies’ quantitative methods and findings are given in this report’s appendix, it is possible to delve more deeply into the approaches taken in its three hedonic regression models for Philadelphia, West Chester, and Pittsburgh. While differences in data availability certainly played a role in variation among the models’ structures (i.e. which predictor variables were included), the need for a compelling and straightforward narrative must have also played a role in each model’s development.

A closer look at the Philadelphia neighborhood included as a case reveals a robust model, with transaction data extending to before 1985, when the sample district of Powelton Village was added to the National Register of Historic Places.28 The inclusion

28 Ibid., 62-65.
of historic data extending back this far, as well as the level of detail about the model itself that is given in the appendix, indicates that Econsult would have had access to additional data that is not currently publicly available, but that would improve similar modeling approaches. This model still does not account for the use of the Federal Rehabilitation Tax Credit at the individual property level, a variable that could potentially be built from multiple data sources but that might not offer sufficient predictive strength to be included in a model, although it has had a clear and visible impact on this particular neighborhood. The other two cases (in West Chester and Pittsburgh) are sketched out much more generally in the report’s appendix, making it challenging to draw conclusions about these two models and the data included in them.

An earlier study by Econsult, completed for the Preservation Alliance for Greater Philadelphia, focused solely on the City of Philadelphia and identified premiums associated with both local and national district designation. The model built for this report also found that increases in transaction prices were sustained, with properties in designated districts continuing to appreciate more rapidly than other similar properties in Philadelphia beyond the initial year of district designation. Additionally, the study found a positive association between proximity to (rather than just location within) a designated historic district, although this scale of analysis might not make sense in a city like

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29 The dataset used in this thesis, which is available on OpenDataPhilly, includes transactions dating back to 1999. It is available as the file “Real Estate Transfers” at https://www.opendataphilly.org/dataset/real-estate-transfers, most recently accessed by the author on August 23, 2019.

30 Although it would be challenging to assemble this information into a single consistent dataset, it would theoretically be possible to track the exact dollar amount received in Federal Rehabilitation Tax credits for each transaction within a geographic area over time (adjusted for inflation). This could then be used to build a model in which each tax credit dollar would be associated with a particular change in property value. The sample size of transactions would likely be too small for this to be meaningful, however.
Philadelphia where nearly half of all properties are located within a mile of a local historic district, as shown in Figures 1 and 2, above.31

**Other Quantitative Studies Evaluating Property Values**

This approach of using hedonic regression to identify associations between a particular condition and property values is widely used in city planning and adjacent fields. In addition to studies looking at historic designation as a factor in determining property values, other studies evaluate the associations with commercial corridors, land vacancy, access to transportation, affordable housing, and even airport noise. In part because these reports take a range of forms, including white papers and academic articles, some delve more deeply into their methodological approaches than others, and all can be used to help determine the level of detail that might be appropriate for future reports in historic preservation, whether looking at designation and property values or at other policy tools.

For example, a 2015 report by Jonathan Wiley analyzes the association between commercial land uses and residential property values in the Atlanta metropolitan area, with 0.5, 0.75, and one-mile boundaries used to define proximity.32 Additionally, this study uses matched samples, meaning that each property transaction included in the model within the boundary is matched with a similar transaction in the same zip code and from the same quarter and year, but that is outside of the given historic district boundary. The level of detail given in the report allows the reader to understand how the model actually works, rather than simply stating the results as fact. An explanation of the

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31 Historic Preservation Activities in Pennsylvania, 22-23.
project’s methodology includes the model’s assumptions, a mathematical equation showing how distance is measured, and a schematic form of the model itself, with groups of variables shown and explained further in the text, all given within the body of the paper.33

“The Economic Impact of Greening Urban Vacant Land: A Spatial Difference-in-Differences Analysis” by Megan Heckert and Jeremy Mennis compares changes in transaction prices over time between a “treatment group” of properties that was greened through the Pennsylvania Horticultural Society’s LandCare program and a control group made up of other unbuilt properties in Philadelphia. Because the LandCare program primarily treats properties that are located in lower wealth communities, and in close proximity to schools, commercial corridors, or other sites of interest, control group properties were selected with these criteria in mind. At the same time, these additional properties needed to be sufficiently far away from actual LandCare properties, in case proximity conferred its own benefit in the form of increasing value.34 This report, more than any other surveyed, examines spatial autocorrelation as part of its approach through the inclusion of geographically weighted regression as well as the use of separate models for each of seven geographically-defined districts in Philadelphia. This approach, in which the association is measured in a range of neighborhood types, aligns closely with the quantitative case study in Section 4 of this thesis. The authors of this report found that the variable of interest to be significant only in distressed areas, but not in the other

neighborhood typologies. An in-depth discussion of the qualitative conditions of individual areas, and of the model’s limitations, also adds substantial richness to the report’s findings.

Residential Stability and Foreclosures

A 2011 University of Pennsylvania thesis by Kimberley Broadbent (now Chantry) explores whether local district designation in Philadelphia was associated with lower rates of mortgage foreclosures in single family homes during the nationwide housing crisis of 2007-2011. By comparing mortgage foreclosure rates between October 2009 and September 2010 in six local historic districts and comparable neighborhoods, this thesis finds that in three cases, the designated district performed better (meaning that the foreclosure rate was lower) than comparable neighborhoods, in two cases, the designated district performed similarly to its comparables, and in one case, it performed worse, indicating additional factors at play. Despite these findings, the thesis focuses most heavily on the positive cases, identifying a “93% greater propensity for single-family residential foreclosure in comparable neighborhoods than in historic districts.”

This past thesis recognizes issues with small sample sizes, given that most of the neighborhoods studied contained fewer than 1,000 single family homes at the time of writing, and one, the Diamond Street local historic district in North Philadelphia, contained as few as 38. A total of two residential foreclosures during the study period

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37 Ibid., 69. See also each chapter’s summary table that shows the designated district and comparable neighborhoods side-by-side.
38 Ibid., 71.
gave a foreclosure rate of 52.6 per 1,000 properties, while the next highest neighborhood had ten foreclosures in total, for a rate of 16.5 per 1,000.\textsuperscript{39} The author acknowledges but does not attempt to correct for this limitation, or for demographic differences among neighborhoods. This project does, however, offer a strong framework from which further studies could build. While its focus is on homeowners and not renters, this type of approach looks at the actual implications of changing property values for Philadelphia residents, extending beyond broadly framed economic impacts to address more nuanced dynamics.

General studies of displacement and residential stability explore systemic conditions, in some cases focusing on theoretical groundings and in others, on particular policies and their implications for homeowners, renters, and/or developers. Ingrid Gould Ellen and Katherine O’Regan’s chapter “Gentrification: Perspectives of Economists and Planners” in \textit{The Oxford Handbook of Urban Economics and Planning} offers a theoretical structure through which to discuss models of neighborhood change, citing models forth by both planners and economists from the mid-twentieth century onward.\textsuperscript{40}

A 2017 article by Lance Freeman and Jenny Schuetz, “Producing Affordable Housing in Rising Markets: What Works?” takes a critical look at major U.S. housing programs, including the Low Income Housing Tax Credit (LIHTC) and Housing Choice Vouchers, as well as at developers’ inclusionary zoning models, to unpack what affordability means in these contexts, and particularly how long it lasts. The authors

\textsuperscript{39} Kimberly Broadbent, “Assessing the Impact of Local Historic District Designation on Mortgage Foreclosure Rates,” 49.
delve into precisely what gentrification looks like when considering renters as compared to homeowners, writing

If gentrification does not necessarily lead to increased rates of direct displacement, it poses for localities at least two other challenges related to housing affordability. First, if gentrification causes exclusionary displacement, which the available evidence suggests, the housing affordability problem boils down to the location of housing that is affordable… Declining affordability in gentrifying neighborhoods could prove disruptive for poor residents and for the businesses and services that relied on those residents as clientele (Meltzer, 2016; Parker, 2016)… Beyond housing affordability, gentrification can also engender feelings of being “pushed out” among long-term residents. As used here, pushed out refers to the disempowerment felt by long-term residents in reaction to their neighborhood changing in ways over which they had little control or say and are ultimately not intended for their benefit.41

These considerations, which are often expressed in the literature around gentrification and displacement, must be brought more fully into the historic preservation discourse, including into discussions of historic designation and property values, where concerns of NIMBYism are widespread but less frequently discussed in academic contexts within the field.

**Related Studies**

While studies of the association between historic district designation and property values make up the bulk of the analyses described in this thesis, additional types of projects are also worth looking to in order to better understand the role of data collection and analysis in the field of historic preservation. Architectural surveys, typically conducted on a citywide scale, rely heavily on data management; project developers must decide which building characteristics to track, and then develop a system to collect and store large

quantities of data in an organized and accessible manner. These studies can be comprehensive surveys of all historic resources within a municipality (or at another geographic scale), or they can focus on a particular building type, construction method, or time period. In recent years, best practices in survey approaches have been developed around data management softwares and approaches, with SurveyLA and the Arches software developed by the Getty Conservation Institute emerging as a best practice.\textsuperscript{42}

While the process of architectural survey relies heavily on data collection and management, recent academic articles that incorporate data analysis into their findings include work in historic preservation as well as allied fields (like city planning and economics) that have historically relied more heavily on data-driven approaches.

For example, a study by Stephanie Ryberg-Webster and Kelly Kinahan of the Federal Historic Rehabilitation Tax Credit’s impact on housing affordability and displacement looked at twelve cities, selected based on data accessibility and the authors’ familiarity with each, and with an eye toward legacy cities with weaker market conditions. Their chapter within \textit{Preservation and the New Data Landscape}, “The Possibilities and Perils of Data-Driven Preservation Research: Lessons from a Multiyear Study of Federal Historic Rehabilitation Tax Credits,” offers detailed information about quantitative approaches without getting bogged down in their explanations. The authors refer to hot-spot analysis to identify spatial clusters, tests for spatial autocorrelation, and

\textsuperscript{42} See Janet Hansen and Sara Delgadillo Cruz, “Big City, Big Data: Los Angeles’s Historic Resources” and Matthew Hampel, “Managing Historic Complexity: Practical Lessons from Tech-Forward Historic Resource Surveys,” both in \textit{Preservation and the New Data Landscape}, for more information on current approaches to architectural survey.
the use of the Herfindahl-Hirschman Index to assess market concentration. Footnotes offer additional insight into the particular approaches employed in the study. In drawing conclusions from their quantitative findings, the authors interpret their results to develop a meaningful narrative without overstating the significance of their findings. They acknowledge substantial limitations in the data and offer recommendations for further study.

A closer analysis of six legacy cities included in the initial group of twelve also includes a cluster analysis, in which neighborhoods in each city are classified into one of eight groups depending on a range of characteristics. These eight groupings are categorized into one of two higher-level clusters identified as stable neighborhoods or ones experiencing high levels of distress. This method, in which all neighborhoods within a city are classified into one of several clusters, could provide an opportunity for an alternative approach to understanding historic designation and property values; this possibility is explored further in “Limitations and Opportunities for Further Study” in Section 4 of this thesis.

43 Hot-spot analysis examines the spatial density of a variable, often in a visual manner. Spatial autocorrelation refers to the positive or negative association between objects or events that are physically near to one another, with greater proximity associated with a stronger association; this relationship can be measured and/or included in a model as an additional predictor variable. The Herfindahl-Hirschman Index is used to measure the market share of a business in relation to others in an area.

LOCAL CONTEXT

Just as differences among municipal historic preservation ordinances mean that local historic district designation looks different from one city to the next, it is also important to recognize additional factors that impact local real estate trends. In Philadelphia, the Philadelphia City Planning Commission, the Philadelphia Historical Commission, City Council, the Zoning Board of Adjustment, the Department of Commerce, the Office of Housing and Community Development, and the Office of Property Assessment together constitute most of the governmental forces whose actions directly impact and reflect current trends in planning, preservation, and development.

Philadelphia2035

Philadelphia recently underwent a comprehensive planning process. The product, Philadelphia2035, includes a Citywide Vision in addition to eighteen district plans. Each of these is built on three interconnected themes: Thrive, which addresses economic development and land management, Connect, which includes transportation and utilities, and Renew, which deals with historic preservation, open space, and the public realm. Housing priorities outlined in the Citywide Vision and carried through into district plans include the stabilization and upgrading of existing housing units, as well as ensuring that units are available at a range of price points throughout the city, in order to reduce concentrations of poverty, expand options for people seeking housing, and build on existing neighborhood assets.45

Updated Zoning Code

Following a 2007 voter referendum, Philadelphia’s zoning code was rewritten for the first time since 1962. The new code, which was developed by the Zoning Code Commission (a temporary body created for this purpose) and implemented in 2012, had the following goals as its framework:

- Provide consistency and understandability of the zoning code.
- Make future construction and development more predictable.
- Encourage high quality, positive development.
- Preserve the character of existing neighborhoods.
- Involve the public in development decisions.46

Today, zoning remapping occurs when a stakeholder – a community group, the local district council member, or the Philadelphia City Planning Commission (PCPC) – requests that current land uses in an area be surveyed and that zoning be reevaluated, either because current land uses do not match zoning, or because changes to land use and zoning may be appropriate. PCPC staff create maps of existing conditions and proposed zoning, and after presentation at a public meeting and endorsement from the PCPC, proposed zoning changes are introduced to City Council and presented to the Mayor. Following a public hearing, a rezoning bill is voted on by City Council and sent to the Mayor for signature.47

46 City of Philadelphia, “Zoning Matters Website,” accessed June 16, 2019, https://www.phila.gov/CityPlanning/projectreviews/PDF/Zoning_Matters_website_CONTENT.pdf, 19. This document was created from a webpage that was available on the City of Philadelphia’s website during the zoning remapping process. It is currently available as a PDF on the “Zoning Resources” section of the PCPC’s website.
47 For a more complete summary of the process, see “Zoning Matters Website,” 6-7.
Registered community organizations (RCOs) play a central role in the process, as the entities that are required to be informed of proposed zoning variances, and that communicate directly with property owners located within 250 feet of any requested variance that will be heard by the Zoning Board of Adjustment (ZBA). Furthermore, they are often directly involved in developing remapping proposals. While the current RCO system was established within the 2012 zoning code changes, many organizations that serve as RCOs existed long before the formalization of their relationship with zoning in Philadelphia.\(^{48}\)

As part of the Philadelphia2035 process, the entire city was remapped according to the newly adopted zoning code.\(^{49}\) In each district plan, recommendations include zoning to reflect existing and desired land uses (called “corrective” zoning in the plans) as well as “zoning to advance the plan,” which are changes to align zoning with proposed and desired land use.\(^{50}\) The Zoning Code Commission created three new zoning districts – CMX2.5 for neighborhood commercial areas, IRMX for industrial-residential mixed use, and SP-AIR, a special purpose airport district – while reducing the overall number of zoning districts.\(^{51}\)

Citywide rezoning as part of the comprehensive planning process was intended to reduce the number of appeals submitted to the Zoning Board of Adjustment, which saw an average of more than 1,500 appeals annually between 2008 and 2012. While the


\(^{49}\) This process may still be underway.

\(^{50}\) “Zoning Matters Website,” 7.

\(^{51}\) Ibid., 19.
percentage of requested variances that were approved has held steady at around 90 percent from 2008 to 2017, the ZBA has seen a decrease in appeals overall, meaning that the actual number of variances granted has gone down since the new zoning code was implemented. Because the percentage of zoning permits approved by right increased from an average of 65.5 percent of all applications in the four-year period leading up to the new code to 71.7 percent in the following five years, the ZBA has seen fewer appeals overall in recent years.52

**Property Assessment**

An audit of the Philadelphia’s Office of Property Assessment’s methods, conducted following a 2019 assessment in which property values increased by an average of 10.5 percent, found major inconsistencies in the process.53 In particular, properties under $100,000 were found to be over assessed, and assessments for one- to four-family homes, commercial properties, and industrial properties did not meet industry standards. Additionally, similar properties (even on the same block) were not assessed consistently, meaning that otherwise similar neighboring properties might have widely disparate assessed values.54

Issues with property assessments are not new to the City. In 2014, Philadelphia instituted the Actual Value Initiative (AVI), which is intended to match assessed value to market value for properties citywide. *The Philadelphia Inquirer* study conducted in 2008

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52 “Five Year Review of the Zoning Code: August 2012 – August 2017.” Percentages calculated from Table 1, page 5.


54 Ibid.
found assessments to be off by an average of 39 percent at that time. The Inquirer’s more recent study of the property assessment process found more than 165,000 single family homes (representing one third of all such properties citywide) to be over assessed, and 133,000 to be under assessed, with lower assessments generally favoring higher-valued properties (Figure 4). The official audit conducted by J.F. Ryan Associates found similar issues, supporting widespread concerns over problems with the assessment process and results.

Figure 4: The Philadelphia’s Inquirer’s review of the 2019 property reassessment.

![Figure 4: The Philadelphia’s Inquirer’s review of the 2019 property reassessment.](source: The Philadelphia Inquirer (August 10, 2018, in “165,000 Philly Homeowners”))

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While the J.F. Ryan Associates audit outlined major problems in the assessment process and results, it did not offer actionable recommendations for improving the system; City Council has issued its own set of recommendations, however, including to hire new leadership and additional staff in the Office of Property Assessment, and to work with external appraisal firms to improve the process and results.56

**Ten Year Property Tax Abatement**

Philadelphia’s ten-year tax abatement was established in the late 1990s to incentivize development in the city, which had been losing population since the mid twentieth century. Given high construction costs in the city, the abatement helps incentivize developers to invest in Philadelphia, as it means that the increase in property value associated with new construction or substantial renovation is not taxed for the first ten years after an investment is made.

While the tax abatement applies to all real estate in Philadelphia, critics of the program argue that it disproportionately benefits properties at the high end of the market – properties valued at more than $700,000 represent seven percent of those qualifying for the abatement but more than half of the value of the tax benefits.57 Proponents of the program claim that the tax abatement encourages investment in the city that contributes to a larger tax base, while critics argue that the benefits are primarily experienced by developers, rather than to the public at large. A 2018 proposal to increase property taxes

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56 Merriman, “Audit Finds Flaws in OPA’s Methods.”
in response to the School District of Philadelphia’s 105-million-dollar deficit led to renewed debate over whether the tax abatement should be discontinued or phased out.\textsuperscript{58}

Given that the majority of Philadelphia voters oppose the abatement (according to a spring 2019 poll by the \textit{Philadelphia Inquirer}) the program’s critics have offered a range of recommendations, from ending the abatement altogether, to phasing it out, to targeting specific types of development. This last approach could distinguish based on property type, value, location, or other factors, including, potentially, favoring rehabilitation over new construction.\textsuperscript{59}

\textbf{Philadelphia’s Housing Action Plan}

The City’s first official housing plan, \textit{Housing for Equity: An Action Plan for Philadelphia}, was published in 2018. Central to Philadelphia’s housing strategy is the idea that a wide range of housing options, at a variety of price points, is needed to serve current and future residents. Given that the city is expected to add 25,000 new households over the next ten years, new housing units will need to be created through a combination of new construction and housing rehabilitation. \textit{Housing for Equity} places particular emphasis on both affordable housing and the rehabilitation of existing structures and

proposes a target of 3,650 new housing units to be created and 6,350 units to be preserved each year.\textsuperscript{60}

Between 2008 and 2016, Philadelphia lost units at the lower end of the market and gained units at the higher end, exacerbating challenges faced by lower income households that were already overwhelmingly rent-burdened (Figure 5, on the following page).\textsuperscript{61} According to the 2013-2017 American Community Survey five-year estimate, nearly half of all Philadelphia households experienced rent burden, spending at least 30% of their income on housing costs; of those households, 58% experienced severe rent burden, spending at least half of their income on housing. This burden is felt most heavily by lower- and middle-income households: a full 85% of Philadelphia residents earning less than $35,000 annually experience rent burden, compared to less than 4% of households earning at least $75,000. Furthermore, although households earning less than $20,000 annually experienced a slight decrease in rent burden from 2009 to 2017, rates of rent burden grew substantially among households earning between $20,000 and $75,000 over this period (Figure 6, page 36).\textsuperscript{62}


\textsuperscript{62} U.S. Census Bureau ACS 2013-2017 Five Year Estimate. According to HUD’s definition of rent burden (more than 30% of income spent on housing), an apartment renting at 800 dollars per month would be affordable to a household earning 32,000 dollars annually, while one at 2,000 dollars per month would be affordable to one earning 80,000 dollars annually.
Certified Local Governments

Philadelphia is one of more than two thousand municipalities that are part of the National Park Service’s Certified Local Government (CLG) program, meaning that they follow a set of state and federal requirements, including through having an historic preservation commission and local ordinance, and facilitating public participation in the local preservation.63 Among other benefits, being a CLG means that locally designated income-producing properties (both individually-designated as well as contributing properties in local historic districts) are eligible for federal tax credits under the Federal Rehabilitation Tax Credit program, which requires that a property designated on the

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National Register of Historic Places, and that the rehabilitation meets the Secretary of the Interior’s *Standards for Rehabilitation*. While typically only National Register (and not state or local) listings for individual buildings qualify for the Federal Historic Preservation Tax Credit program, income-producing buildings in CLGs that contribute to a locally designated historic district may also qualify, provided that the local government’s criteria for historic district designation and treatment review are certified by the Secretary of the Interior.

**Figure 6: Rent burden by annual household income in Philadelphia, 2009-2017.**

*Graphic by the author*

*Data source: U.S. Census Bureau ACS 2005-2009 and ACS 2013-2017 five-year estimates*
Designation in Philadelphia

The Philadelphia Historical Commission (PHC), which is part of the City’s Department of Planning and Development, maintains the Philadelphia Register of Historic Places, reviews building permit applications for changes to listed properties, and advises property owners and the public about preservation techniques and resources. While PHC staff approve more than 90 percent of permit applications (often through an iterative process with the property owner, developer, and/or architect) and without needing to move to a committee vote, more complex and/or contentious projects are presented for review at bimonthly public meetings.64

After an extended period of very limited local historic designation, both on the district and individual property scale, six local historic districts have been designated since 2017. While part of this change has been attributed to a staffing increase in Philadelphia’s Historical Commission and greater efficiency due to changing municipal regulations, local advocacy efforts have also had an impact.

Looking more broadly at political power in Philadelphia, the strength of the city’s councilmanic system plays a central role in the designation process; in 2004, Representative Jannie Blackwell of District 3 raised concerns over potential adverse effects that designation might have on low- and moderate-income residents within her district. As part of this process, Representative Blackwell proposed a change to the city’s historic preservation ordinance that would have given city council increased oversight of

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the designation process; this discussion set a precedent that local historic districts would be challenged going forward, effectively discouraging further attempts at designation.65

**Philadelphia Historic Preservation Task Force**

Established by Mayor Kenney in May 2017, the Philadelphia Historic Preservation Task Force recently completed an evaluation and recommendation process for four key areas: survey of historic resources, incentives for preservation, regulations for preservation outcomes, and outreach and education. The task force, which consisted of 33 members, including preservation professionals (both academics and practicing professionals) as well as developers, community advocates, and city representatives, explored the impacts of local historic designation, as well as the potential for changes to the city’s preservation ordinance that could offer additional protections to properties and/or new incentives to owners of contributing buildings in local historic districts, as well as to individually listed buildings.

Of particular note was a discussion about potential changes to local district designation that would offer more tailored designation levels, depending on individual districts’ characteristics and the input of area residents. Similar in some ways to the three classifications of designation in the England (Grade I, Grade II*, and Grade II), such an approach would allow for more flexible regulations and incentives in districts that might not require the full level of regulation that is offered through what is often perceived to be the current “one size fits all” approach to local designation in Philadelphia. Drawing from

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65 Jannie Blackwell lost in the May 2019 primary to Jamie Gauthier, after more than 25 years in office. Gauthier, who most recently served as the Executive Director for Fairmount Park Conservancy, will run unopposed in the November election.
the use of Neighborhood Conservation Districts, which offer an opportunity for community groups to develop guidelines for new construction with input from the Philadelphia City Planning Commission, such an approach could potentially mitigate resident and homeowner concerns about new construction, while loosening restrictions related to building alterations, even of historic properties.

In considering the incentives that would be associated with different types of local designation, the Task Force proposed that districts with more stringent regulations should also offer greater incentives to owners. While this might encourage more restrictive and highly protective designation, it is important to consider which types of districts would be more likely to receive this level of designation compared to less restrictive forms. If higher wealth communities are more likely to designate to the level with both greater restrictions and higher incentives – because such neighborhoods may be more likely to be designated on the basis of architectural significance and aesthetic value than other historic districts – then these communities would have access to more financial capital through incentives than those that could benefit more from additional support.

Additionally, the Task Force recommended that all buildings within local historic districts be categorized as contributing, noncontributing, or (a new category) significant, to more fully capture the variation within a given district. While these categories would guide the level of design oversight to be placed on individual buildings, a block’s overall character would also be considered in establishing appropriate levels of regulation.

67 Ibid., 21.
QUANTITATIVE APPROACH

This study pairs three sets of physically and demographically similar neighborhoods to create three separate linear regression models, all with the same sets of predictor variables. Unlike other economic impact studies on historic district designation that compare designated and undesignated properties across an entire city, this approach highlights the diversity of local historic districts within Philadelphia and looks to draw closer comparisons between similar pairs of neighborhoods. This method, which could be considered either as a set of three case studies or a modified randomized block design using hedonic regression, uses sales transactions data from the City of Philadelphia, with sales prices as the dependent variable. It attempts to mitigate some of the issues associated with directly comparing disparate neighborhoods, as each of the three pairs (and their associated models) consists of two similar neighborhoods, one designated and the other not.

While typical hedonic regression pricing approaches include building and neighborhood characteristics as variables, that approach does not offer the flexibility to assign different coefficient values to a single variable depending on other predictor variable values (in this case, a categorical variable identifying the particular neighborhood or local historic district in which a property is located). By running separate regressions for each neighborhood-district pair, it is possible to identify whether

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68 This report uses ordinary least squares (OLS) regression, which is the most commonly used and intuitive type of linear regression.
69 The methodological approach used to create the model follows the loose structure of a randomized block design, albeit without randomization, as the “treatment” of historic designation is not assigned randomly within each pair of neighborhoods but is rather based on designated district and recognized neighborhood boundaries.
70 Each of the three designated neighborhoods correspond to local historic districts that are also listed on the National Register of Historic Places.
there may be opposing trends among the three groups. For example, one neighborhood pairing may have seen an increase in transaction values between 2001 and 2007, whereas another pair’s transaction values may have remained steady – the three separate regressions can account for these nuances in a way that a single model would not.

This chapter is designed as a proof of concept, with the recognition that an analysis of transaction values from a subset of a single city is not sufficient to establish broad findings. Nevertheless, it addresses gaps in previous studies and sets the stage for a more rigorous approach moving forward. Most importantly, it makes room for a more nuanced understanding of and conversations around the potential associations between local historic district designation and property sales prices or value.

Beginning with a brief summary of how linear regression models work, this chapter then moves into a detailed explanation of how neighborhood pairs were identified, and variables selected. The results are interpreted for each of the three pairings. For clarity, these pairings and their associated models are referred to as the Center City model (for Society Hill and Bella Vista), the Fairmount model (for Parkside and Strawberry Mansion), and the Schuylkill-Northwest model (for Manayunk and East Falls). Finally, limitations are addressed and recommendations made for further study.

**Linear Regression**

A linear regression model determines the mathematical relationship among a collection of predictor variables associated with a set of observations, which in this case are
individual residential property transactions. The resulting function consists of a y-intercept and several variables, each with its own coefficient that weights that variable’s contribution to the overall transaction value, holding all other variables constant. By plugging values into the equation for each variable, one obtains an expected transaction value for a given property at a particular time.

A general linear regression model can be written as:

\[ y = \beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k + \varepsilon \]

Here, \( y \) represents the dependent variable (residential sales price), \( \beta_0 \) is the y-intercept, and \( \beta_i \) represents the coefficient for each independent variable from 1 through \( k \). An interpretation of \( \beta_i \) (for \( i > 0 \)) is that for each one unit increase in the predictor variable, the value of the dependent variable is expected to increase by \( \beta_i \) units, holding all other predictors constant. For example, if the number of bedrooms is a predictor variable in a regression model, then for each additional bedroom, the sales price can be expected to increase by the coefficient’s number of dollars, holding everything else constant.

Note that the line of best fit, which is given by the main equation above with the error term removed, does not represent the exact relationship among the variables for the full population, but rather an approximation of that relationship using the available data. Because it is impossible to reduce transactions to a finite set of measurable variables, the linear regression equation cannot perfectly predict each transaction’s exact price. Furthermore, a model that could do that would be said to be overfit, meaning that the

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71 It is not possible to distinguish whether a property is income-generating from the dataset (see page 13 for a more detailed explanation of this limitation).
72 James, et al., *An Introduction to Statistical Learning with Applications in R* (New York: Springer Science+Business Media, 2013), 63-65.
model’s coefficients would be too closely aligned with the existing data, and the model would erroneously treat anomalies in the dataset as meaningful.

To test a model’s performance, one can remove a portion of the full dataset’s observations before building the model using the observations that remain, which are collectively called the training set. By then running the model on the testing set (those observations that were removed), one can see how well the model performs on data that it has not yet seen. In the case of this project, one could randomly select ten percent of all property transactions in each of the six neighborhoods to remove, build the models using the remaining transactions, and then enter values for the predictor variables in each of the transactions that were initially removed.

By comparing the transaction values as predicted by the model to actual transaction records, it would be possible to see how well the models perform on those transactions that were not used to build the model. This would be done by looking at the final term in the regression equation, which is the residual, written as $\varepsilon$. The residual is assumed to be normally distributed and have a mean of zero. In the form of an equation, the residual for each individual observation (sales transaction) $i$ is:

$$
\varepsilon_i = y_i - \hat{y}_i
$$

Where $\hat{y}_i$ is the expected transaction value based on the equation above, and $y_i$ is the actual (observed) transaction price.

**Understanding Regression Outputs**

The regression output includes values that allow one to evaluate whether the relationships among variables are significant. The F-ratio test evaluates whether there is likely to be an
association between the full set of predictor variables and the dependent variable. The p-value gives the likelihood of obtaining the observed f-value if the null hypothesis ($H_0$) is true. In this case, the null hypothesis is that none of the predictors is associated with the dependent variable, and the alternative hypothesis is that at least one predictor (not necessarily that of local historic district designation) is in fact associated with the dependent variable of transaction value. A p-value of <0.05 means that there is less than a five percent chance that the null hypothesis is true given the observed data; this would allow for the rejection of the null hypothesis, meaning that there is likely to be an association between at least one predictor in the model and residential sales prices in Philadelphia.

The process of building a model is an iterative one, with predictor variables added and removed as they are checked for statistical significance. While some variables, like building square footage or the number of bedrooms in a house, are fairly common to see in other studies of property values or transaction prices, others might not appear in other models as frequently. Variable selection can depend on many different factors, including predictive strength (as measured by the regression output), data quality (meaning that certain variables may be more likely to contain errors), and ease of interpretation.73

The r-squared value given as part of the regression output indicates the portion of the dependent variable that can be explained by the collection of predictor variables included in the model. This number, which ranges from zero to one, offers insight into a model’s predictive power, as a value of one would indicate that the model predicts all

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73 In Philadelphia, the building construction year is an example of a variable that may be more likely to contain errors, given the use of 1915 and 1925 as estimates where precise records do not exist (see Figure 12 on page 64).
variation in transaction prices. In the social sciences, an r-squared value of 0.5 or higher is generally considered sufficient to indicate moderate correlation, although models with lower values (of around 0.3 or 0.4) are still used. An r-squared value of 0.5 can be interpreted as meaning that 50 percent of the variance in the dependent variable can be explained by the set of predictor variables.

P-values associated with each predictor variable are also part of the regression output. Asterisks appear next to each as a quick visual check for significance, although variables can be included even if they are not statistically significant. Furthermore, a variable’s significance (and its coefficient) will change as the model is adjusted. Adding or removing one variable will affect the others in a model, which is why one might try several different configurations before settling on the final model.

Neighborhood Selection

In contrast with existing studies on historic districts, in which all designated properties (or all properties within a local historic district) are compared with all other properties in a city, this project directly compares three pairings of physically and demographically similar neighborhoods, using sales transactions data from the City of Philadelphia. This approach mitigates some of the issues associated with directly comparing disparate neighborhoods, as each of the three pairs consists of two neighborhoods that are similar in both physical form and socioeconomic characteristics.

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74 In more theoretical contexts, an r-squared value of 0.8 would generally indicate a strong model, and values could be even higher than that.

75 Additionally, variables (some or all predictor variables and/or the dependent variable) can be transformed using mathematical operations to normalize their distribution. This process is not used in this thesis, largely for simplicity and clarity.
Selection Criteria

There are a total of twenty one local historic districts in Philadelphia, although two of them – the Historic Street Paving Thematic District (designated in 1998) and the Ridge Avenue Roxborough Thematic Historic District (designated in 2018) – are geographically dispersed and were not evaluated as part of this study (Figure 7, on the following page). Of the remaining nineteen, a subset of districts was selected for further study, based on the total number of properties included within each of their boundaries, and with geographic, demographic, and physical diversity in mind.

Selection criteria for the three designated districts included:

- A sufficient number of properties located within each district;
- Consistency among the three districts as to whether they also overlap with a nationally designated historic district;
- Substantial differences in character among the three districts, including geographic dispersion, a range of socio-economic identities, and the overall character/level of architectural integrity in the historical district itself;
- Potential neighborhoods to serve as non-designated pairing for each.

While these criteria may have initially seemed overly broad, they addressed key needs for both consistency among and differences between the three pairings. More importantly, they left room for more informal knowledge of Philadelphia to inform the final pairings.
In thinking about potential non-designated pairings for selected designated districts, the following criteria were considered:

- **Geographic**: distance to Center City
- **Access to amenities**: presence of universities or other major institutions nearby; proximity to Fairmount Park and/or smaller neighborhood parks

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76 The Historic Street Paving Thematic District and the Ridge Avenue Roxborough Thematic Historic District are not shown, as they are both noncontiguous. Note also that Parkside is a locally designated historic district, despite the fact that its boundaries are smaller than those used in the model.
- **Built environment**: building scales and diversity; residential/commercial/industrial land use mix; physical (spatial) barriers such as bridges or tunnels

- **Socio-economic**: racial and ethnic backgrounds; household income levels

- **Neighborhood stability**: homeownership versus rental rate; length of tenure in the neighborhood; student presence

U.S. Census Bureau American Community Survey 2013-2017 data provided core demographic data, albeit with the limitations that come with using census tract boundaries to approximate study areas. Physical neighborhood characteristics were observed through publicly available shapefiles as well as in-person observation.

*District-Neighborhood Pairs*

Although there are substantial limitations to using census tract boundaries to gather information around households and housing units in the six selected districts/neighborhood geographies, U.S. Census Bureau data is a readily accessible and interpretable dataset. The boundaries of the Manayunk historic district proved particularly challenging however, as they do not align with census tract boundaries (Figure 8). Despite these limitations, census tract data, a polygon-based shapefile of Philadelphia buildings, and knowledge of the local context provided the basis for determining the three sets of matched pairs to include in the analysis.

Society Hill, Manayunk, and Parkside historic districts are representative of the diversity of the city’s local historic districts, and two of the three (Society Hill and Manayunk) were designated prior to the start of the study period; the third, Parkside, was
designated in 2009. All three are also National Register Historic Districts, with Society Hill designated in 1971, and Manayunk and Parkside in 1983. For the purposes of this study, Parkside’s boundaries are extended beyond those of the local historic district to include the National Register Historic District boundaries, as the local district’s boundaries do not produce a sufficient number of property transactions for the regression analysis.

Figure 8: The Manayunk local historic district overlaps with four census tracts but does not make up the majority land area for any one of them.

Although it would ideally be possible to consider only those local historic districts that are not also nationally designated, the limited number of local historic districts in Philadelphia makes this impossible. Additionally, because National Register Historic Districts are not mapped by the National Register of Historic Places, and because most of
their nomination forms are not digitized, there are barriers to identifying the boundaries of National Register Historic Districts in sufficient detail. Furthermore, a focus on local designation allows for both a greater attention to owner-occupied residential properties as well as an approach that acknowledges hyperlocal factors that are at play in evaluating local historic districts, as described earlier in this thesis.

Bella Vista was selected as a match to Society Hill because of its geographic proximity, physical characteristics, and lack of other planning or preservation tools that might have muddied the comparison. Given that many of Center City’s residential properties are in designated historic districts, there were only a few possibilities for this pairing. Queen Village, which might have otherwise been selected, is a designated Neighborhood Conservation District.

Parkside and Strawberry Mansion were identified as a strong pair early in the process. Both neighborhoods include grand twins and larger buildings that front Fairmount Park (on either side of the Schuylkill River), as well as more modest rowhouses elsewhere in the neighborhoods. A robust presence of long-term residents and active community organizations characterize the neighborhoods. Both also suffer from historical disinvestment, and experience issues related to tangled titles (especially due to ownership not being formally transferred to family members with the owner’s passing), aging-in-place, and a lack of resources for building maintenance.

The pairing for Manayunk was more challenging, as the comparison neighborhood that was ultimately selected actually does include a local historic district. For the purposes of this study, East Falls’ boundaries were drawn to exclude the properties located within that district, as other possible comparables were too different.
from Manayunk to be used for direct comparison using this approach. A few key characteristics for full set of neighborhood pairs appear in Figure 9, on the following page.

**Data Preparation**

The City of Philadelphia’s Department of Records dataset of real estate transfers, released on OpenDataPhilly in January 2018, forms the core of this analysis. A total of 3.75 million observations representing transactions recorded since December 1999 are included, with information related to grantors and grantees, assessed and fair market value, and transaction and recording data, among a total of 48 variables.

**Data Sources**

In addition to the real estate transfers dataset, the model incorporates a building footprint shapefile from the Department of Records as well as a property data shapefile from the Office of Property Assessment. While not used in the final model, American Community Survey 2013-2017 five-year estimates obtained through American FactFinder and additional datasets (all available on OpenDataPhilly) were used to illustrate similarities within and differences among the three sets of neighborhood pairs.

**Data Cleaning**

Initial data cleaning in the open source statistical software and programming language R included the removal of unnecessary fields and the standardization of others, leaving a total of 23 variables remaining. Property sales occurring outside of the six
### Figure 9: Neighborhood comparisons.

<table>
<thead>
<tr>
<th>Neighborhood</th>
<th>Racial Makeup</th>
<th>Ownership Rate</th>
<th>Legacy Residents (Moved pre-1979)</th>
<th>Avg Bldg Height</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Philadelphia</strong></td>
<td>42% White</td>
<td>52%</td>
<td>11%</td>
<td>23.5 ft</td>
</tr>
<tr>
<td>(Baseline for Comparison)</td>
<td>15% Black</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Society Hill</strong></td>
<td>92% White</td>
<td>63%</td>
<td>5%</td>
<td>33 ft</td>
</tr>
<tr>
<td></td>
<td>8% Black</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Bella Vista</strong></td>
<td>70% White</td>
<td>48%</td>
<td>6%</td>
<td>27.5 ft</td>
</tr>
<tr>
<td></td>
<td>13% Black</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Parkside</strong></td>
<td>4% White</td>
<td>34%</td>
<td>15%</td>
<td>25.5 ft</td>
</tr>
<tr>
<td></td>
<td>9% Black</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Strawberry Mansion</strong></td>
<td>6% White</td>
<td>32%</td>
<td>18%</td>
<td>27 ft</td>
</tr>
<tr>
<td></td>
<td>94% Black</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Manayunk</strong></td>
<td>64% White</td>
<td>51%</td>
<td>11%</td>
<td>27.5 ft</td>
</tr>
<tr>
<td></td>
<td>19% Black</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>4% Asian</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>4% Other Races</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>East Falls</strong></td>
<td>67% White</td>
<td>44%</td>
<td>9%</td>
<td>24.5 ft</td>
</tr>
<tr>
<td></td>
<td>13% Black</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Graphic by the author

Data Sources: U.S. Census Bureau ACS 2015-2017 five-year estimate; Philadelphia Department of Records
selected neighborhood boundaries were removed from the dataset, leaving 65,040 property transactions. Within each neighborhood, observations representing sales not considered to be arms-length transactions were removed from the dataset, leaving only those transactions likely to have been made by unrelated buyers and sellers, and sold for fair market price. In practice, this was done by excluding records in which the sales price or market value is below 1,000 dollars. Transactions of commercial, industrial, or vacant properties were also removed (Figure 10).

**Figure 10: Transaction data by neighborhood.**

<table>
<thead>
<tr>
<th>NEIGHBORHOOD</th>
<th>LOCALLY DESIGNATED?</th>
<th>NUMBER OF OBSERVATIONS (TRANSACTIONS INCLUDED IN THE MODEL)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>CENTER CITY</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Society Hill</td>
<td>Y</td>
<td>3,043</td>
</tr>
<tr>
<td>Bella Vista</td>
<td>N</td>
<td>2,653</td>
</tr>
<tr>
<td><strong>FAIRMOUNT</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Parkside</td>
<td>Y&lt;sup&gt;78&lt;/sup&gt;</td>
<td>988</td>
</tr>
<tr>
<td>Strawberry Mansion</td>
<td>N</td>
<td>777</td>
</tr>
<tr>
<td><strong>SCHUYLKILL NORTHWEST</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Manayunk</td>
<td>Y</td>
<td>156</td>
</tr>
<tr>
<td>East Falls</td>
<td>N&lt;sup&gt;79&lt;/sup&gt;</td>
<td>1,577</td>
</tr>
</tbody>
</table>

*Table by the author*

*Data Source: City of Philadelphia*

<sup>77</sup> This was done through a spatial join of the transaction data to a shapefile created for this project using Azavea’s neighborhood boundaries and local district boundaries. The areas included for Parkside and East Falls were modified slightly, as described in the body of this report, and in the following footnotes.

<sup>78</sup> The boundaries used in this model include the local historic district but extend beyond it, to ensure a sufficient number of observations.

<sup>79</sup> While there is a local historic district associated with East Falls, the area included in the model does not overlap with this district.
Variable Selection and Omission

The overwhelming majority of variables considered for the model are associated with individual parcels, rather than with census tracts or neighborhoods. While census data was considered in the neighborhood selection process, tract boundaries are arbitrary, reducing gradual shifts in an area’s characteristics into sharp artificial boundaries.

A Department of Records shapefile offers data on building height and density, which was used in the identification of appropriate neighborhood comparisons. These variables were aggregated based on neighborhood boundaries as defined in a shapefile created by the Philadelphia-based geospatial technology firm Azavea, and some were used in the final model, with all transactions within a single geographic zone receiving the same values. Although neighborhood boundaries, like census tract boundaries, are arbitrary, larger neighborhood zones flatten out some of the more abrupt transitions that occur on the census tract level. Additionally, because Azavea’s neighborhood boundaries were used to determine the boundaries of the non-designated pairings, data aggregated to this level more accurately reflects the reality of those geographies. While the challenges in defining neighborhood boundaries in Philadelphia have been explored in recent news articles, Azavea’s boundaries frequently appear in planning reports and local news sources, and a better source for determining neighborhood boundaries in Philadelphia does not exist.  

The imbalance in numbers of transactions between geographic zones is considered acceptable but not ideal, as the geographic zone with the fewest transactions,
Manayunk, includes 156 transactions distributed over the nineteen-year period.

Transactions are grouped into the following sets of years, with the groupings included in the regression model as dummy variables: 1999–2003, 2004–2008, 2009–2013, and 2014–2018, to reflect patterns in the U.S. real estate market over time.\textsuperscript{81} By analyzing change over time, it is possible to begin to tease out whether historic designation might be associated with increased or decreased sales prices (relative to similar areas), as well as potentially with increased or decreased stability in sales prices, given that the U.S. real estate market experienced a major shock during this time period.

**Data Analysis and Results**

A series of three linear regressions were run, one for each of Center City (Society Hill and Bella Vista), Fairmount (Parkside and Strawberry Mansion), and Schuylkill-Northwest (Manayunk and East Falls). In order to allow for a more direct comparison among the models, and by extension, among the coefficients associated with the local district designation in each, the same set of predictor variables was included in each of the three models. These variables are:

- Type of property (multifamily, single family, mixed-use)
- Central air conditioning (a binary variable)
- Exterior condition (a numeric variable on a scale of 1 to 5, as evaluated by the Office of Property Assessment)

\textsuperscript{81} A dummy variable is a variable that gives a value of 0 or 1, depending on whether the statement is true. For example, a transaction occurring in the year 2005 would have values of “0” for the variable 1999-2003, “1” for 2004-2008, “0” for 2009-2013, and “0” for 2014-2018. The coefficients associated with each of the variables assigned to 0 do not contribute to the predicted transaction value for a given observation, while the remaining variable’s coefficient does.
- Number of fireplaces
- Frontage, in feet
- Number of garage spaces
- Interior condition (a numeric variable on a scale of 1 to 5, as evaluated by the Office of Property Assessment, with many NAs)
- Number of bedrooms
- Number of bathrooms
- Number of stories
- Total area
- Total livable area
- Year built
- Zoning category
- Whether the observation is located in one of the locally designated neighborhoods (Society Hill, Parkside, or Manayunk) or in one of the comparison neighborhoods (Bella Vista, Strawberry Mansion, or East Falls)

The full regression outputs for the three models, given in Figure 11 on the following page, include the coefficients and levels of significance associated with each of these models for each variable, along with the R-squared and adjusted R-squared values.

Typically, the coefficients for the historic district variable would be the most important regression output. In this set of models, these coefficients could be interpreted as indicating that designation is associated with a $306,700 increase in transaction prices.
### Figure 11: Regression outputs for the three models.

#### Center City Model

| Coefficient | Estimate | Std. Error | t-value | Pr(>|t|) |
|-------------|----------|------------|---------|----------|
| (Intercept) | 1,954.064 | 240.774 | 8.1374 | 0.00000438 *** |
| category_ZN Misc Use | -65.3 | 220.204 | 0.30 | 0.770983 |
| category_built_from | -46.267 | 239.794 | 0.20 | 0.840301 |
| category_zn from | 71.109 | 239.794 | 0.30 | 0.770983 |
| category_ZN Recent | 825.395 | 478.549 | 1.73 | 0.081381 |
| central_ac | -23.312 | 15.668 | -1.47 | 0.149848 |
| central_heat | 49.932 | 17.557 | 2.83 | 0.004842 * |
| exterior_c | -18.253 | 30.554 | -0.6 | 0.549652 |
| fireplace | 54.734 | 10.621 | 5.08 | 0.003726 *** |
| floorarea | 118 | 9.040 | 13.13 | 0.0000000000000037 |
| garage_area | 117.502 | 13.792 | 8.59 | 0.0000000000000037 |
| garage_depth | 67.502 | 30.653 | 2.24 | 0.025207 |
| bedrooms | 7.628 | 5.667 | 1.34 | 0.186203 |
| bathrooms | -16.093 | 8.504 | -1.9 | 0.059561 |
| number_rooms | 30.690 | 4.164 | 7.35 | 0.0000000000000037 |
| total_area | 49.0 | 4.529 | 10.80 | 0.0000000000000037 |
| year_built | -599 | 90 | -6.66 | 0.0000000000000037 |

#### Fairmount Model

| Coefficient | Estimate | Std. Error | t-value | Pr(>|t|) |
|-------------|----------|------------|---------|----------|
| (Intercept) | 1,780.275 | 448.846 | 4.02 | 0.0000000000000037 |
| category_ZN Misc Use | 50.876 | 62.705 | 0.81 | 0.418661 |
| category_built_from | -16.311 | 62.302 | -0.26 | 0.792077 |
| category_ZN Recent | -15.632 | 101.207 | -0.15 | 0.879912 |
| central_ac | 50.876 | 62.705 | 0.81 | 0.418661 |
| central_heat | 49.932 | 17.557 | 2.83 | 0.004842 * |
| exterior_c | -18.253 | 30.554 | -0.6 | 0.549652 |
| fireplace | 31.534 | 249.818 | 0.13 | 0.999952 |
| floorarea | -15.632 | 101.207 | -0.15 | 0.879912 |
| garage_area | 156.635 | 55.379 | 2.83 | 0.006106 ** |
| garage_depth | 32.609 | 72.703 | 0.45 | 0.652716 |
| bedrooms | -12.485 | 15.103 | -0.81 | 0.418661 |
| bathrooms | -51 | 56.900 | -0.91 | 0.370543 |
| number_rooms | 26.168 | 10.006 | 2.62 | 0.008842 |
| total_area | 53 | 23 | 2.29 | 0.023388 * |
| year_built | -39.9 | 39.271 | -1.01 | 0.318216 |

#### Schuylkill-Northwest Model

| Coefficient | Estimate | Std. Error | t-value | Pr(>|t|) |
|-------------|----------|------------|---------|----------|
| (Intercept) | 1,599.264 | 336.459 | 4.77 | 0.0000000000000037 |
| category_ZN Misc Use | 15.197 | 29.795 | 0.53 | 0.598942 |
| category_built_from | -81.173 | 29.606 | -2.74 | 0.006142 *** |
| category_ZN Recent | -95.112 | 809.093 | -0.12 | 0.909031 |
| central_ac | -51.150 | 28.093 | -1.85 | 0.068643 * |
| central_heat | -40.169 | 24.965 | -1.58 | 0.117275 |
| exterior_c | -32.387 | 33.904 | -0.96 | 0.341362 |
| fireplace | 22.413 | 21.235 | 1.08 | 0.281534 |
| floorarea | 1.860 | 516 | 0.35 | 0.729560 |
| garage_area | 21.543 | 10.689 | 2.02 | 0.044008 * |
| garage_depth | 10.673 | 33.393 | -0.30 | 0.764924 |
| bedrooms | 5.845 | 5.279 | 0.99 | 0.345991 |
| bathrooms | 2.855 | 6.548 | 0.44 | 0.657045 |
| number_rooms | -2.246 | 4.191 | -0.53 | 0.595123 |
| total_area | -2 | 5 | -0.38 | 0.705933 |
| year_built | 227 | 310 | -0.71 | 0.477243 |

**Table notes:**
- Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.1 ‘.’ 1
- Residual standard error: 39230 on 5635 degrees of freedom
- Multiple R-squared: 0.4486, Adjusted R-squared: 0.4478
- F-statistic: 31.77 on 23 and 5635 DF, p-value: 0.0000000000000037

**Model summary:**
- Model created using the statistical software R. See Appendix for the code used to produce the model.
in Center City, a $34,600 decrease in the Fairmount neighborhoods, and a $8,400 increase in the Schuylkill-Northwest neighborhoods. This set of values is not meaningful, however, given major limitations in all three models. Of the three models, Center City is the only one for which the p-value associated with the historic district variable indicates that the variable is statistically significant. Despite this indication of significance, even the staunchest advocates for the positive association between historic district designation and property values would be hard-pressed to argue that designation is associated with such a large increase in sales prices.

Because this project’s goal is not to develop a strong model, but rather to lay the groundwork for more thoughtful and cautious use of data, this is as far as the modeling itself is taken. The following section of this report, which explores limitations and opportunities for further study, delves further into these issues.

**Limitations and Opportunities for Further Study**

As described above, a limited number of observations and a limited set of predictor variables means that these models are not particularly robust. R-squared values of 0.5117, 0.3974, and 0.6012 for the Center City, Fairmount, and Schuylkill-Northwest pairings, respectively, indicate that the predictor variables explain between 40 and 60 percent of the variation in sales prices, depending on the pair of neighborhoods in question. Despite this, the historic district designation variable is only statistically significant in the Center City regression, but not in the others.

The model explored in this thesis is meant as a preliminary exploration of how one might think more creatively about developing quantitative studies in historic
preservation, and certainly not as a definitive model to be used going forward. The following concepts and approaches should be explored in greater depth, while acknowledging that quantitative findings will always be at best just one piece of a broader discussion around historic district designation, and rarely, if ever, determinative in and of themselves.

**Spatial Autocorrelation**

A major limitation of these models, and one that is common to most of the studies surveyed for this project, is that the spatial relationships among data points are not explicitly considered. This relationship, known as spatial autocorrelation, is based on Waldo Tobler’s First Law of Geography, which states “Everything is related to everything else, but near things are more related than distant things.”

Typically, data displaying autocorrelation display a positive spatial relationship, meaning observations located near to each other have similar values for a variable; in this example, property transactions physically near one another are more likely to be similar.

Although there are multiple ways to test for spatial autocorrelation, the technique of Moran’s I is the most common. This approach calculates a value that typically ranges from -1 to +1, with values close to -1 indicating negative spatial relationships, values close to +1 indicating positive spatial relationships, and values close to zero indicating that there is likely no spatial relationship in the data.

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To correct for spatial autocorrelation, a spatial lag or spatial error model could be used to more explicitly account for the spatial component of the data. Both of these types of models are meant to account for the role of spatial relationships in the data that are incorrectly included in the error term in linear regression (given as \( \varepsilon \) in the equation on page 44). In a spatial error model, the residuals from OLS regression are regressed on the residual values of nearby observations, thereby separating the OLS regression residual into the part that displays a spatial component and “random noise,” which is part of any model that is built using a finite number of observations. In a spatial lag model, the values of the dependent variable at nearby observations are included as a separate predictor variable in the model. In the case of this project, this would mean including the average transaction value for some number of nearby transactions a predictor variable.

*Use of a Training and Testing Set*

A stronger model would ideally be built using only a subset of the data available, so that it could then be tested on the observations that were removed earlier in the process. A comparison of the values predicted by the model with the known values would be used to evaluate the model’s strength, and to determine whether it performed better on a particular subset of observations (i.e. higher or lower valued properties). This was not attempted for this project due to the limited number of transactions in several of the selected neighborhoods, as it would have further reduced the size of the model’s training set.
A Matched Pair Approach

A matched pair approach, in which each transaction would be matched with a similar one (both temporally and spatially), would allow for greater precision but would potentially suffer from an insufficient number of data points, particularly if neighborhood pairings were continued to be used. As described by Wiley in *The Impact of Commercial Development on Surrounding Residential Property Values*, “Matched samples increase the precision of the comparison between subject and control group observations at the expense of lower statistical power (due to fewer observations). The results are noticeably sensitive with respect to choice of radius and matching criteria.”

Thoughtfulness in Assigning Labels

While the three neighborhood pairs selected for this thesis represent three different neighborhood typologies, they were intentionally not labeled as high income, middle income, and low income (or wealth) groups, as this would have been an oversimplification of their conditions that would have added an implied layer of judgment to the interpretation. Instead, if one wanted to explore dynamics among different income groups or rentership levels, it could make sense to assign every residential census tract into the city to one of several groups on the basis of that single variable, both to lessen the discomfort with flattening neighborhoods into a single defining characteristic as well as to increase the number of observations to be included in the model.

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84 Here, “residential census tracts” is meant only to exclude a very limited number of census tracts, including those in which the city’s two airports are located.
Looking Beyond Local Historic Districts

In addition to the city’s 21 designated local historic districts, additional geographic areas have been nominated for designation over the years. These areas, including 33rd Street along East Fairmount Park in Strawberry Mansion (included in this thesis as an undesignated neighborhood) and Spruce Hill in West Philadelphia, offer compelling potential comparison groups, as they are areas that have been formally recognized for their historic value (by virtue of being considered for designation), but are not impacted by the oversight given by actual designation.

A study incorporating both local historic districts as well as non-designated neighborhoods that have received other form of recognition for historical significance, including through Neighborhood Conservation Districts (e.g. Queen Village), or Main Street programs (e.g. Tacony) could offer additional information, although the limited amount of data available may make this challenging. Additionally, one could explore differences in trends within designated historic districts with properties immediately outside of them. This would allow for greater control over differences between the groups than the approach taken in this report.

A Note on Data Collection and Quality

Any quantitative model is only as strong as the data that is used to build it. Data quality issues include both inconsistencies and inaccuracies within existing city datasets as well as a lack of data collection, particularly related to historic resources. As more cities, including Philadelphia, begin to plan more seriously for comprehensive historic survey, it will be important to ensure that data management practices allow for smooth integration
of past survey work into the process, and for data to be consistently maintained and updated over time.

Beyond a grounding in quantitative methods from a theoretical standpoint, historic preservationists would benefit from a deeper understanding and appropriate use of locally available datasets. In Philadelphia, datasets offering property- and parcel-level data can contradict one another, adding challenges beyond theoretical data analysis and modeling. For example, parcel boundaries drawn by the Philadelphia Water Department differ from those from the Department of Records, neither of which corresponds directly with property records from the Office of Property Assessment (OPA). Even beyond the difficulties in combining separate datasets, inconsistencies within a single source can introduce uncertainty into the accuracy of individual variables. Recorded building construction years are approximated when they are not known and rounded to the nearest decade (Figure 12, on the following page), but they are also sometimes fully incorrect. While a construction date that is off by a year or two does not pose major issues, the OPA’s dataset reports that there are fewer than 9,000 residential buildings in Philadelphia constructed before the year 1900; an in-depth survey of the neighborhood of Strawberry Mansion found at least 1,700 such properties in an area of less than one square mile.85 These types of issues are outlined more broadly in the chapter by Andrew Dolkart in *Preservation and the New Data Landscape*.86

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85 Research conducted as part of a studio course in historic preservation, fall 2017. In addition to the properties included in this count are at least 4,000 properties constructed between 1895 and 1910, also within Strawberry Mansion.

Perhaps more concerning in the case of this project (which relies on property sales data over a twenty year period), data entry errors can mean that even transaction years are incorrect – a quick look into recent property transactions in Philadelphia revealed at least one property with a transaction date in the future (with 2019 given instead of the actual year of 1919).

Figure 12: Number of properties by construction year as recorded by the City of Philadelphia’s Office of Property Assessment, with peaks at five-year intervals.87

Additionally, because the property-related variables in the Office of Property Assessment are updated on a monthly basis, building characteristics included in the data may not reflect conditions at the time of sale, particularly for older transactions. Ideally,

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87 This graph shows all properties with the OPA category code of “1,” corresponding to single family residential buildings, beginning in 1854 when the City of Philadelphia was consolidated. An additional 2,303 properties with this category code have construction years prior to 1854, and 621 have construction years of “0,” to indicate unknown.
the City or another organization would keep records of older datasets for use in this type of context to further strengthen our understanding of property conditions, as it would allow for an understanding of the state of each property at the time of sale, rather than in the present day.
POLICY IMPLICATIONS AND CONCLUSIONS

From a policy perspective, the value in using a quantitative approach is based on its flexibility and potential for applicability in a range of city contexts. This also means, however, that it is impossible to capture the full nuance of what it means for a place to be designated and regulated as historic. Although an understanding of hedonic regression methods can and should be an expectation among professionals working in preservation planning, these approaches cannot be used as the sole or primary defense for preservation policy. Claims that designation will lead to positive economic outcomes open the discussion up for opposing findings that could then overpower other, potentially positive outcomes, including ones that are not economic in nature.

Perhaps most concerning is the possibility that quantitative studies conducted on the neighborhood scale (as is done in this report) could be used as part of the evaluation process for an individual area under consideration for historic district designation. Such an approach would lay the groundwork for designation to become a tool only applied to particular types of neighborhoods, perhaps those in which households already have the resources to invest freely in physical upkeep.88

Looking Beyond Property Value

A deeper understanding of the dynamics at play in different types of neighborhoods could be used in the development of more targeted tools to support communities in locally designated historic districts. For example, if a more robust model were to find differences

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88 This concern is also apparent when considering that different levels of incentives could potentially be tied to different types of local historic designation, if less restrictive forms of designation were to be introduced.
in the association between designation and property values in owner-occupied compared to renter-occupied residences, policymakers could strengthen an argument for a specialized set of incentives that could better respond to residents’ (whether property owners’ or renters’) needs.89

Federal Rehabilitation Tax Credits and Designation

As outlined in Section 3 of this thesis, the Federal Rehabilitation Tax Credit program (also known as the Historic Tax Credit or Historic Preservation Tax Credit program and abbreviated as HTC) is a major incentive for historic designation on the National Register. This program, which offers a twenty percent income tax credit for qualifying rehabilitation projects of historic buildings, has contributed to a total of more than 44,000 rehabilitation projects since it was established in 1976, corresponding to nearly 97 billion dollars of investment in historic properties. In fiscal year 2018 alone, 6.9 billion dollars of private investment was spent on projects ranging in size from under 250 thousand to more than 25 million dollars.90

The benefits offered through the Federal Rehabilitation Tax Credit program (as well as the State Historic Preservation Tax Credit program, which is currently available in 35 states, including Pennsylvania) are a major incentive for historic district designation, as designation unlocks the potential for tax credits for incoming-generating properties. In the neighborhood of East Parkside, for example, the potential for tax credits

89 As described on page 13 of this thesis, this distinction would be almost impossible to make on a property level, although an approach similar to the one used in this thesis could be used to separate local historic districts into groups based on overall rentership versus owner occupancy rates.
led resident and developer James Brown IV and the Parkside Historic Preservation Corporation (PHPC) to get Parkside designated to the National Register of Historic Places in 1987, making it eligible for historic tax credits that Mr. Brown used to help make his investments financially viable, shaping investment patterns in the neighborhood over the past forty years.

Because of the close connection between designation (on the National Register of Historic Places, but also on local registers in certified local governments) and historic tax credits, concerns are sometimes raised that designation might incentivize the conversion of owner-occupied houses into rental properties. While there is not anything inherently negative about rental properties, these concerns are sometimes tied to a changing neighborhood character, whether through the introduction of large developers or through a fear of lower income households moving in, as well as to a perception that renters may be less invested in their neighborhoods than are homeowners. A recognition of these concerns, and of their implications, is central to understanding the true impact of historic district designation, beyond its impact purely on property values.

**Rising Value, Affordability, and Displacement**

As Freeman and Schuetz point out in “Producing Affordable Housing in Rising Markets,” incentives for producing affordable residential units for homeownership typically stipulate only a limited period of affordability, with fifteen years for the required initial compliance period in the case of LIHTC, for example. With this in

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mind, advocates for housing affordability are increasingly calling for programs that either support renters (as these are less often term limited, whether they follow the household, as in voucher programs, or are tied to the property) or for ones that extend the period of affordability for ownership properties.\(^{92}\) Such programs in the latter group might include community land trusts and limited equity cooperatives.\(^{93}\)

In their data-driven study of the Federal Rehabilitation Tax Credit program (HTC), Ryberg-Webster and Kinahan recommend greater integration among affordable housing incentives and HTC; while housing developers often use LIHTC and HTC together, they combine the HTC program with Section 8, Section 202, and HOME less frequently – this is a missed opportunity that could potentially shift with increased integration among affordable housing programs and incentives for historic preservation; while such a process would no doubt require substantial challenges from both the regulatory and administrative perspective, it would have the potential to have a real impact on the role of historic preservation in affordable housing development.\(^{94}\)

_Renter Protections_

Renter protection, in the form of stronger state or local legislation, could both improve physical conditions in rented units as well as offer protections against rapidly rising rents and/or formal or informal evictions. While the concept of renter protections is not generally seen as a tool for historic preservation (but instead one for housing preservation, which generally refers to the preservation of affordability), recent shifts in

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\(^{92}\) Lens and Reina, “Preserving Neighborhood Opportunity,” 718-720.

\(^{93}\) Freeman and Schuetz, “Producing Affordable Housing in Rising Markets,” 224.

the discipline of historic preservation are beginning to recognize how interrelated the two truly are. The decoupling of one from the other (historic preservation from housing preservation and affordability) is a false dichotomy that flattens a complex relationship and contributes to concerns that historic preservation is about the built fabric and aesthetic qualities above all else.95

Given the dynamics of ownership and rentership described throughout this thesis and in the affordable housing literature, it is imperative that historic preservation advocates begin to engage more with this issue. While rental units introduce the potential for changes to buildings’ physical fabric, and to uncertainty more broadly, greater alignment between historic preservation and housing preservation will strengthen the role of each. Philadelphia recently introduced a bill to allow accessory dwelling units (ADUs) in historically designated properties, a move that could support homeowners (as ADUs must be part of owner-occupied properties) by offering an additional income stream, while expanding the stock of affordable rental housing.96

Final Thoughts

Through an in-depth case study, this thesis has aimed to demonstrate both the need for deeper engagement with quantitative methods as well as an appropriate level of skepticism of their potential role in developing and critiquing policy decisions. This case

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study, which explored the complicated association between local district designation and transaction values in Philadelphia without glossing over the messiness of the data and findings, aims to illustrate the need for future practitioners to become more comfortable sharing and interpreting complex findings. An understanding of quantitative methods cannot and should not replace policy expertise, but should rather supplement it – while there is a danger in relying too heavily on quantitative findings (particularly considering how they are so rarely as clear cut as they may initially appear), widespread gains in data literacy will add new tools from which historic preservationists can draw, ones that are already part of the common language in adjacent fields.
BIBLIOGRAPHY


James, Gareth, Daniela Witten, Trevor Hastie and Robert Tibshirani. An Introduction to Statistical Learning with Applications in R. New York: Springer Science+Business Media, 2013.


_____.


Nijkamp, Peter. “Economic Valuation of Cultural Heritage” in The Economics of Uniqueness, 75-106.


___. “Heritage Conservation and Property Values” in *The Economics of Uniqueness*, 107-142.


APPENDIX: R CODE

This code, created by the author, can be used as a starting point for further exploration of
the association between local district designation and transaction values in Philadelphia.

```r
# Note that some data manipulation, particularly of
# neighborhood boundaries, was completed in ArcMap
setwd("Insert_filepath_here")
rm(list=ls())
options(scipen=999)

install.packages('dplyr')
install.packages('tidyverse')
install.packages('tidyr')

library(dplyr)
library(tidyverse)
library(tidyr)

Sales <- read.csv("RealEstateTransfers_Philadelphia.csv")
# From OpenDataPhilly

########################################################################
# INITIAL DATA CLEANING #
########################################################################

# Fields to keep:
# Sales values
# Sales$cash_consideration  # transaction amount
# Sales$other_consideration  # what is this?
# Sales$total_consideration  # based on cash + other
### End up using Sales$total_consideration

# Too many NAs, but keep for now
# Sales$adjusted_assessed_value
# Sales$adjusted_fair_market_value
# Sales$assessed_value
# Sales$adjusted_cash_consideration

# Fields to remove:
# Tax-related
Sales$local_tax_amount <- NULL
Sales$local_tax_percent <- NULL
```

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Sales$state_tax_amount <- NULL
Sales$state_tax_percent <- NULL
Sales$adjusted_local_tax_amount <- NULL
Sales$adjusted_state_tax_amount <- NULL
# Not relevant
Sales$recording_date <- NULL # display date uses recording date sometimes, but use display date
Sales$receipt_date <- NULL
Sales$receipt_num <- NULL
Sales$discrepancy <- NULL
Sales$document_id <- NULL
Sales$legal_remarks <- NULL
# Location-related (will use xy coordinates or street address instead)
Sales$street_predir <- NULL
Sales$street_name <- NULL
Sales$street_suffix <- NULL
Sales$street_postdir <- NULL
Sales$unit_num <- NULL
Sales$address_low <- NULL
Sales$address_low_frac <- NULL
Sales$address_low_suffix <- NULL
Sales$address_high <- NULL
Sales$condo_name <- NULL
Sales$ward <- NULL
Sales$zip_code <- NULL
# Too many NAs
Sales$common_level_ratio <- NULL

# Clean transaction date field
Sales$display_date <- sub(" .*", ",", Sales$display_date)
names(Sales)[names(Sales)=="display_date"] <- "trans_date"
Sales$trans_year <- sub("-.*", ",", Sales$trans_date)

########################################################################
# BUILDING VARIABLES ####################################################
########################################################################

# Only includes OPA property data within the six neighborhoods
# This was done in ArcMap
OPA_Data <- read.csv("OPA_forR.csv")

# All sales associated with the six neighborhoods
# Add building characteristics, from OPA_Data
Data <- merge(Sales, OPA_Data, by.x="opa_account_num", by.y="parcel_num")

# Remove extra fields from shapefile
Data$grantors <- NULL
Data$grantees <- NULL
Data$FID <- NULL
Data$Join_Count <- NULL
Data$TARGET_FID <- NULL
Data$objectid.y <- NULL
Data$house_numb <- NULL
Data$book_and_1 <- NULL
Data$building_c <- NULL
Data$building_1 <- NULL
Data$garage_type <- NULL
Data$geographic <- NULL
Data$location_1 <- NULL
Data$owner_1 <- NULL
Data$owner_2 <- NULL
Data$parcel_n_1 <- NULL
Data$registry_1 <- NULL
Data$registry_2 <- NULL
Data$registry_3 <- NULL
Data$registry_n <- NULL
Data$objectid_1 <- NULL

# Rename fields
names(Data)[names(Data)="$number_of1"] <- "bathrooms"
names(Data)[names(Data)="$number_o_1"] <- "bedrooms"

# Add sales year intervals
Data$trans99_03 <- ifelse(Data$trans_year=="1999", 1, 0)
Data$trans04_08 <- ifelse(Data$trans_year=="2004", 1, 0)
Data$trans09_13 <- ifelse(Data$trans_year=="2009", 1, 0)
Data$trans14_18 <- ifelse(Data$trans_year=="2014" | Data$trans_year=="2015" | Data$trans_year=="2016" | Data$trans_year=="2017" | Data$trans_year=="2018", 1, 0)
Data$histdist <- ifelse(Data$DIST=="SOHI" | Data$DIST=="PARK" | Data$DIST=="MANA", 1, 0)

# Filter out transactions of less than $1000 (looking for arms-length sales only)
# Filter out vacant land, and commercial and industrial properties

CC <- Data %>%
  filter(.,, DIST=="SOHI" | DIST=="BEVI") %>%
  filter(.,, total_consideration > 1000) %>%
  filter(.,, category_c==1 | category_c==2 | category_c==3)

Fairmount <- Data %>%
  filter(.,, DIST=="PARK" | DIST=="SMAN") %>%
  filter(.,, total_consideration > 1000) %>%
  filter(.,, category_c==1 | category_c==2 | category_c==3)

NW <- Data %>%
  filter(.,, DIST=="MANA" | DIST=="EAFA") %>%
  filter(.,, total_consideration > 1000) %>%
  filter(.,, category_c==1 | category_c==2 | category_c==3)

###############################################################
################### BUILDING THE MODELS #########################
###############################################################

regCC <- lm(total_consideration ~ category_2 + central_ai + exterior_c + fireplaces + frontage + garage_spa + interior_c + bedrooms + bathrooms + number_sto + total_area + total_liva + year_built + zoning + trans99_03 + trans04_08 + trans09_13 + trans14_18 + histdist, data=CC)
summary(regCC)

regFairmount <- lm(total_consideration ~ category_2 + central_ai + exterior_c + fireplaces + frontage + garage_spa + interior_c + bedrooms + bathrooms + number_sto + total_area + total_liva + year_built + zoning + trans99_03 + trans04_08 + trans09_13 + trans14_18 + histdist, data=Fairmount)
summary(regFairmount)

regNW <- lm(total_consideration ~ category_2 + central_ai +
   exterior_c + fireplaces + frontage + garage_spa +
   interior_c + bedrooms + bathrooms + number_sto + total_area
   + total_liva + year_built + zoning + trans99_03 +
   trans04_08 + trans09_13 + trans14_18 + histdist, data=NQ)
summary(regNW)

###########################################################
############### SUMMARY TABLES OF OPA DATA ###############
###########################################################

# Used to make Figures 2 and 12 in this report

OPA <- read.csv("OPAapr2019.csv")
names(OPA)

Summary_YR.BUILT <- OPA %>%
   group_by(YR.BUILT, CAT.CD) %>%
   summarize(count = n())

Wide_YrsBuilt <- spread(Summary_YR.BUILT, YR.BUILT, count)
write.csv(Wide_YrsBuilt, file = "SummaryYrBuilt.csv")

Dist <- read.csv("Distance_histdist.csv")

Summary_Distance <- Dist %>%
   group_by(category_c, QtrMi, OneMi, TwoMi) %>%
   summarize(count = n())
write.csv(Summary_Distance, file = "SummaryDistance.csv")
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