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Computer Assisted Mass Appraisal: Algorithmic Discrimination in Philadelphia

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Summary

Property tax burdens disproportionately burden low-income and minority households, exacerbated by overassessment of property. At the same time, local governments face property tax revenue shortfalls, affecting public services. Philadelphia's tax burden distribution and property assessments are particularly criticized by the assessment industry and local advocacy groups, meanwhile its property tax revenues per capita are lower than similar-sized cities. With evidence of overassessments and a delinquency rate nearly double the national average, improvements to the city's mathematical valuation model are expedient.

Public finance theory suggests that property taxation matches residents' property tax bills with local service costs. Research has revealed systematic overassessment across demographics and geography, violating these bedrock principles by skewing revenue distribution and service provision. Establishing whether Philadelphia's overassessment is systematic across certain factors is the primary objective, followed by whether such inaccuracy heightens delinquency and tax foreclosure risk at the household level. The empirical strategy addresses two main objectives using panel data. First, it distinguishes systematic overassessment due to Phildelphia's model from unexplained and random overassessment using random effects regression. Second, it examines if overassessment increases the likelihood of tax delinquency and foreclosure by running time and entity fixed effects panel regression models to estimate predictors of these outcomes.

Systematic overassessment is not solidified, but a share of non-random overassessment is found to change by property style, with row homes, condos, and semi-detached homes being associated with higher overassessment compared to single detached homes. Properties in neighbourhoods with lower median income, higher Hispanic and Black populations, and multifamily zoning designation also see higher average overassessment. Lower median income also puts residents at risk of delinquency, regardless of a property's overassessment. Tax foreclosure odds increase six years after overassessment, though odds are better accounted for by annual factors, for example Philadelphia's Covid-19 measures may have triggered a foreclosure spike in 2021. The need for more household-level data to clarify these trends is noted.

Philadelphia should consider Automated Valuation Models (AVMs) to prevent cases of algorithmic discrimination. Integrating Artificial Neural Networks (ANNs) through add-on software is promising, though geographically weighted regression (GWR) best utilises the current system's modelling capabilities. ANNs offer the greatest overall accuracy while GWR balances targeted overassessment reductions, transparency to residents, and cost. Implementing these recommendations offer reduction in valuation errors by minimising human bias, expanding property data, and including currently omitted variables that affect value.

Keywords

Algorithmic Discrimination, Computer Assisted Mass Appraisal, Delinquency, Overassessment, Tax Foreclosure

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Acronyms

Acronym	Full form
AI	Artificial Intelligence
ANN	Artificial Neural Network
A/S	Assessment Value to Sales Value Ratio
AVI	Actual Value Initiative
AVM	Automated Valuation Model
CAMA	Computer Assisted Mass Appraisal
DoR	Department of Revenue
GIS	Geographic Information System
GWR	Geographically Weighted Regression
HI	Horizontal Inequity
IAAO	International Association of Assessing Officers
MLR	Multiple Linear Regression
OPA	Office of Property Assessment

1. Introduction

1.1 Motivation

Housing costs are increasing at historic annual rates throughout the United States, outpacing wage growth in the past decade (Federal Housing Finance Agency, 2024, p. 5; Guzman & Kollar, 2023, p. 49). Residential property tax bills thus comprise and increasing burden for households. Exacerbating this burden are patterns of overtaxation nationwide, in many cases originating from overassessment of property value. U.S. cities value properties using multiple linear regression models, making these models a subject of academic criticism and taxpayer disapproval.

At the same time, local governments in the U.S. are experiencing increasing shortfalls in property tax revenues (Sirmans et.al, 2008). Being local governments' primary own-source revenue stream, this threatens public expenditure autonomy (Hayashi, 2020; Augustine et. al, 2009). Further, groups that are overassessed over-pay for basic public services funded by the property tax including education and law enforcement. In other words, they are distributed a lower level of public investment than they are owed.

With the highest poverty rate out of the ten largest U.S. cities, sitting at 22.7% (U.S. Census Bureau, 2024), unanticipated increases in Philadelphian's property tax bills may be financially destabilising for a large swathe of the city's population (Fu, 2022). Additionally, Philadelphia's valuation process has been scrutinised for overassessing multifamily properties, of which house a higher share of low-income and minority residents (Hou et.al, 2023; Fu, 2022). The contours of overassessment have yet to be empirically established in Philadelphia, of which are needed to determine assessment process improvements. An opportunity for targeted improvements is present given that Philadelphia's assessment process is in a transitional state.

1.2 Problem Statement

1.2.1 Background and Social Problem

In Philadelphia, property tax revenues per capita are below those of similar sized U.S. cities and are decreasing relative to other local source revenues (Dowdall & Warner, 2012; Hincken, 2022). Philadelphia's low-revenue-generating property tax base is distinctively characterised as increasingly reliant on residential properties. 71% the property tax base is residential, 15% points higher than the U.S. median (Hincken, 2022, pp. 12, 13). This reliance is an outcome of two competing interests. On the one hand, the City of Philadelphia favours low taxes on commercial, retail, and industrial property to increase corporate tax competitiveness (Philadelphia Forward, 2003; Dowdall & Warner, 2012). On the other hand, the property tax is increasingly unpopular among residents, with 76% of residents being against a rate increase in 2022 and 49% rating the property tax as unfair (Hincken, 2022, p.7).

Like the majority of U.S. cities, Philadelphia utilises a computer-assisted mass appraisal (CAMA) system to run a multiple linear regression (MLR) valuation model. This model is limited with respect to property characteristics, overlooking heterogeneous features commonly found outside of single family homes. Industry auditors link this approach to valuation errors given taken the city's diversity of historic property styles (International Assocation of Assessing Officers, 2022, p.9).Thus far there is agreement that Philadelphia's multifamily-zoned homes are overassessed at higher rates, and that these are largely inhabited by minority and low-income groups. This is notable considering Philadelphia is highly spatially segregated first by race and secondarily by income. The Census Bureau's city segregation rankings are based on minority isolation and neighbourhood dissimilarity indices, and ranks Philadelphia with the sixth highest Black-White and Hispanic-White segregation and the twenty-fifth highest Asian-White segregation (Logan, 2013). Adelman (2004) also ranks Philadelphia with the highest within-class racial segregation nationally (p. 51).

Another cause for concern is Philadelphia's nearly 4% property tax delinquency rate compared to the 2% national average, making it the most property tax delinquent big city in the nation (Eichel & Ginsberg, 2019). The city can recover some of its property tax debt by auctioning delinquent properties, but this is considered a collection method of last resort as it displaces residents. If residents in properties that tend to be overassessed fall delinquent because of the unexpected increase in tax owed, they may be at risk of tax foreclosure.

Beyond preventing skewed revenue distribution, there are fiscal benefits and legal requirements for reducing overassessments. These include meeting Constitutional mandates, reducing administrative costs (Alm et.al, 2016), preventing market distortions (McCluskey et. al, 2013; Bahl et. al, 2010), and avoiding litigation. The Office of Property Assessment (OPA) has previously modernised its property tax system in response to these pushes. The 2013 Actual Value Initiative (AVI) was pursued after advocacy pressure and greatly improved assessment practices (International Association of Assessing Officers, 2022), but accuracy improvements were only seen for single family homes in higher income, majority non-White neighbourhoods (Hou et. al, 2023, pp. 16, 17).

1.2.2 Research Problem and Objectives

Public finance theory cites overassessment as a violation of the bedrock Benefits Model, where residents' property tax bills equal the cost of local services they receive (Barseghyan & Coate, 2016, p. 2). To connect the Benefits Model with assessment practice, the literature tests for systematic overassessment. The primary research objective of this study is to test for systematic overassessment in Philadelphia's CAMA system model.

A number of econometric studies test the relationship between general assessment increases, delinquency and tax foreclosure. Fu (2022) does so in Philadelphia, however, only Atuahene & Berry (2019) test and find a relationship between overassessment and the probability of tax foreclosure. Therefore, this study also aims to establish whether overassessment creates an additional financial shock heightening delinquency and tax foreclosure risk for Philadelphia households.

A wealth of related studies provide alternative assessment models to correct for systematic overassessment, but stop short of inquiry into cities' barriers and opportunities for adopting such alternatives. To do so for Philadelphia, methodology documents from OPA and CAMA system handbooks are used. A thorough understanding of OPA's process is required to apply research on alternatives and offer viable policy recommendations.

1.3 Research Questions

The primary research question is the following:

What factors are associated with residential property overassessment, and how is overassessment related to delinquency and tax foreclosure in Philadelphia?

This sub-question is needed to explain the above:

What is the likelihood that overassessed properties become delinquent and reach foreclosure?

1.4 Structure and Reading Guide

Chapter Two covers five areas of the relevant public finance research. Chapter Three outlines how the empirical strategy is employed to answer the research questions through the selected regression models and property data. Limitations are noted. Chapter Four reports results, presents findings as answers to the research questions, and discusses implications alongside remaining research gaps. Chapter Five concludes the study by connecting the findings to assessment policy.

2. Literature review and hypotheses

This literature review begins by laying the theoretical foundation that necessitates assessment accuracy. It then points to potential sources of error in Philadelphia's assessment model and identifies factors commonly found to be systematically overassessed. A discussion follows on the tax delinquency and foreclosure literature, including the gap in connecting these to overassessment. Next is a note on assessment model transitions. To conclude a conceptual framework is presented as a basis for four theoretical hypotheses.

2.1 Theoretical Property Tax Principles

This section introduces property tax fundamentals that and guide an optimal assessment system. First, the foundational Benefits Model posits that residents' property tax bills should act as a user fee and equal the cost of local services provided (Barsheghyan & Coate, 2016, p. 34). This model is a theoretical ideal with the assumption that assessments exhibit not only no overassessment, but also no horizontal inequity (HI). HI in both academic and industry contexts means a property is under or overassessed compared to the property with the most similar characteristics and market value (International Association of Assessing Officers, 2017; Office of Property Assessment (OPA), 2023). To function as a user fee, Berry (2021) argues the property tax must both accurately capture a property's true market value and be based on the ability to pay (p. 22). Ihlanfeldt (2013) points to assessment errors as preventing both (pp. 3,4).

Assessment administration's role in upholding the Benefits Model is understood through two of its principles: fairness and efficiency. The first is fairness, meaning that taxpayers should be protected from "unscrupulous" tax treatment (McCluskey et. al, 2013, p. 164). These protections ensure that assessments capture true market value, free from assessor bias. The second principle is efficiency, which both McCluskey et. al (2013) and Bahl et. al (2010) describe as maintaining local public service delivery without distorting market behaviour. Overassessment above the ability to pay may distort spending, residential location, or real estate investment. Without these principles, the overassessed indirectly subsidise the under-assessed by over-paying for public services the other under-pays for. For example, in the 19th century 22% of property tax revenue from overassessed Black taxpayers in Georgia was disbursed to White majority public schools (Kahrl, 2013, p. 11).

According to the Benefits Model, if the property tax is a user fee, then residents can maximise their utility according to the Tiebout Model, another property tax foundation. Tiebout's (1956) theory explains residential sorting into the tax jurisdiction with the preferred combination of public service level and tax bill. However, Fraenkel (2021) criticises the Tiebout Model as failing to explain the lack of sorting capability for income-constrained residents. These residents respond differently to a tax increase, and the Tiebout Model assumptions fail to hold entirely in cases where the increase is in the form of an overassessment.

Failure to uphold the Benefits and Tiebout Models can generate unpopularity. To avoid this, a CAMA system should maintain the dual components of predictive accuracy and explainability (McCluskey and Adair 1997, p. 2). Inaccurate valuation departs from what taxpayers perceive as their property's "true" market value. An assessment formula's opacity (and unexplainability) to taxpayers then leads to appeals and arbitration (Bahl et. al, 2010, p. 10). Balancing accuracy and explainability is the central challenge of assessment administration.

2.2 Overassessment

Empirical research on overassessment factors, delinquency, and tax foreclosure has surged in the past decade, but the latter two are studied in relative isolation to the former. Most overassessment studies interrogate the assessment process as done by Hou et.al (2023), Sirmans et.al (2008), and Berry (2021). This section first explores these possible bias sources, error sources, and then the factors commonly found to be systematically overassessed.

2.2.1 Bias, Error, and Algorithmic Discrimination

Systematic overassessment from CAMA-based MLR models have been argued as a case of algorithmic discrimination. This concept explains how automated systems such as MLR reflect administrators' biases and can result in de-facto discrimination. OPA's standard MLR model for unsold properties follows this equation:

$$(1)\ Assessment_i = \beta_0 + Adjustments_i \perp \beta + \varepsilon_i$$

$$Adjustments_i = \begin{bmatrix} \text{Property Style} \\ \text{Building Square Footage} \\ \text{Age} \\ \text{Lot Size} \\ \text{Garage Type} \\ \text{Off-Street Parking} \\ \text{Interior Condition} \\ \text{View} \\ \text{Amenity Proximity} \end{bmatrix}$$

Where $Assessment_i$ is property i's valuation, the constant β_0 is the market value proxy for unsold properties in a zone, and $Adjustments_i$ is a vector of property i's characteristics listed in OPA (2023) (p. 9). Unknown market values of unsold properties are imputed using sale values of properties deemed comparable. Comparable properties are selected by drawing geographic zones with properties of least dissimilar characteristics and determining the most representative property within each zone (OPA, 2023, p. 12). This comparable sales value is applied to unsold properties within its zone, then adjustments for physical characteristics are made to arrive at the assessed value (OPA, 2023, p. 12). Sold properties' own sales values are used instead of the zone constant β_0. Non-constant variance in ε_i may indicate property i is over or underassessed compared to the most similar property of the most similar market value.

For algorithmic processes such as the model represented in Equation (1), Kleinberg et. al (2019) distinguish between discrimination originating from the algorithm itself and from the algorithm's designers; the former stemming from mismeasurement of data and the latter from designers' omissions of crucial variables or choice of functional form (pp. 24, 26). Econometric studies including Avenancio-Leon & Howard (2022) and Payton (2014) similarly note two sources of discrimination in CAMA, being structural "model mistakes" and "deliberate distortion" (Avenancio-Leon & Howard, 2022, p. 8). Berry (2021) further argues that model specification mistakes outweigh data accuracy issues, Kahrl (2013) points to both model errors and deliberate distortion as violations of the fairness principle. Table 1 provides a summary of possible biases and errors in the process displayed in Figure 1. These sources are often obfuscated by random assessor error, which is found to creep in through manual tasks (Berry, 2021, pp. 21, 23). For instance, Chun & Linneman (1985) reveal half of overassessment variation in Philadelphia's previous assessment model is attributable to random mistakes (p. 7).

Table 1: Summary of Bias and Error Sources

Model Component	Description	Bias and Error Link
Comparable Sales Value	A zone's comparable property is selected as the property with the least dissimilar physical characteristics within a geographic area (OPA, 2023). Sales values for this property are applied as the market value proxies for all unsold properties in a zone.	Comparable sales values may mis-measure market value for properties with large characteristic deviations. This is concerning given that the fundamental objective of assessment is prediction for out-of-sample (unsold) values (Berry, 2021, p. 20).
Property Characteristic Independent Variables	The comparable sales value is multiplied by a set of adjustments for an individual property's characteristics (OPA, 2023). Assessors have the discretion to manually select which adjustment variables out of the full set to apply to all properties within a zone (International Association of Assessing Officers, 2017, p. 7).	The adjustment variables are limited and best describe single detached features. Omitted variable bias is expected, especially for difficult to observe structural and neighbourhood characteristics that affect true market value (Amornsiripanitch, 2024, p.16).

2.2.2 Overassessment factors

With Equation 1's limitations in mind, research indicates overassessment tends to vary across three main characteristics being structural, locational, and demographic. Regarding property characteristics, overassessment across structural features such as property age and square footage have been identified Allen & Dare (2002). While these are a concerning source of error, many municipalities do indeed specify such characteristcs. Research thus also focuses on a range of omitted structural characteristics that affect market value. Amornsiripanitch (2024) attributes systematic overassessment to structural characteristics omitted due to their difficulty to uniformly observe and measure, for instance structural integrity and interior construction (pp. 3, 16). Limiting these characteristics is argued to manifest in overassessment because they are not used in the selection of comparable properties to use as sales proxies (Amornsiripanitch, 2024, p 16).

It is well established that overassessment also varies by omitted highly localised factors, which are frequently found to cluster by neighbourhood (Bidanset et.al, 2019; Amornsiripanitch, 2024). Cornia & Slade (2005) test for inequity in multifamily homes in Maricopa County, which uses a similar MLR model to OPA. They find that overassessment has the strongest associations with two omitted variables: the number of units in property as a structural characteristic and the number of units in the property's area as a neighbourhood characteristic (Cornia & Slade, 2005, pp. 25, 37). Since restrictive U.S. zoning laws result in economic and racial segregation by zoning density, as found by Rothwell & Massey (2010), and multifamily zoning districts contain a high quantity of high-unit properties, overassessment may cluster in these low-income districts. Using Chicago data, Smith (2008) investigates neighbourhood density using zoning designation speficially to show movement from high density (non-Single family) to medium density (Single family) produces an average decrease in HI of 12.5% (p. 13).

Of the three categories, demographic HI is perhaps the most difficult to trace back to model errors. Berry (2021) finds HI to cluster in areas with higher poverty and minority populations on a national level, and a number of econometric studies reveal systematic HI across demographic factors nationwide, including Avenancio-Leon & Howard (2022), Allen & Dare (2002), and Cornia & Slade (2005). Avenancio-Leon & Howard (2022) find that Black homeowners pay 13% more on average in property taxes per year relative to White homeowners with identically valued properties, and Hispanic homeowners pay up to 10% more (Avenancio-Leon and Howard, 2022, pp. 2, 29). They use neighbourhood fixed effects to explain the mechanism for the disparity across racial and ethnic minorities, income, and location. Segregation and sorting occurs with respect to racial and ethnic minority status, income level, and education level into certain neighbourhoods (Avenancio-Leon & Howard, 2022, p. 30). Highly local features of these minority neighbourhoods are not considered in valuation models nationwide, so resident sorting into neighbourhoods with such omitted features is found to better account for overassessment rather than overt discrimination.

Overassessment research has touched on the Philadelphia context, but not with the same intensity with comparable cities such as Detroit and Chicago. While findings from cities using similar valuation models help develop expectations, these expectations are rather loose given highly localised differences in the physical property stock and neighbourhood composition. Chun & Linneman (1985) conduct the earliest overassessment study in Philadelphia, finding half of the variation to be non-random and concentrated in non-white and low-income neighbourhoods (Chun & Linneman, 1985, p. 5). This is also the first regression analysis across neighbourhood factors in Philadelphia, uncovering a trend of overassessing omitted “undesirable” traits including traffic congestion, high crime rate, and low hospital access (Chun & Linneman, 1985, pp. 9,10).

2.3 Delinquency and Foreclosure

Property tax delinquency occurs when taxes go unpaid in the short-term (one year in the case of Philadelphia), while tax foreclosure occurs when the unpaid debt accumulates across years. Both have been established metrics of financial distress by Bradley (2013), Carroll & Goodman (2017), and Wong (2023), who provide an array of factors that may increase the risk of such. As a value-based tax often unlinked with a taxpayer’s ability to pay, general assessment increases are broadly described as a financial shock increasing delinquency risk. This shock may occur when economic conditions either increase a property’s valuation relative to income or decrease income relative to the valuation. Bahl et. al (2010) offer an underlying economic factor by describing how real estate bubbles rapidly increase homes’ market values relative to incomes, which assessment adjustments do not ‘smooth’ (p. 10). Depressed household incomes as a risk factor have also received considerable attention since the 2008 subprime mortgage crisis. Hayashi (2020) confirms that value increases are more burdensome for low-income and illiquid households (pp. 20, 22). Household-level factors other than income include mortgage status because the "shock" effect of a tax increase is found to amplify when paid as an annual lump sum (Bahl et.al, 2010, p. 10), as is the case for households without a mortgage escrow account (Bradley, 2013, p. 25). In Philadelphia these household-level factors are shown to be procrastination and liquidity constraints (Chirico et.al, 2019, p. 5,7). Delinquency is thus not always financially driven, as Bahl et. al (2010) even point to ideological opposition to the property tax as a driver.

Delinquency is also linked to high unpopularity on the household and neighbourhood level. Unpopularity is commonly measured through appeals volumes, the success of which are partially attributed to assessment explainability. Bird et. al (2012) describes CAMA as a statistical 'black box', rendering it incredibly difficult for taxpayers to provide evidence of overvaluations (Bird et. al, 2012, p. 116). Higher income taxpayers can hire industry appraisers to assist with the technical burden of proof and have higher success rates (Bird et. al, 2012, p. 116). Avenancio-Leon & Howard (2022) and Weber & McMillen (2010) show that Census tracts with a higher minority share have fewer applications and lower success rates. Carroll & Goodman (2017) go on to find low appeals coincide with high neighbourhood delinquencies and foreclosures in high minority neighbourhoods with denser housing in Milwaukee (p. 22). However, no single guiding theory behind delinquency behaviour and neighbourhood features emerges from these studies. In short, research suggests a few key demographic factors on the household and neighbourhood level may both increase the likelihood of overassessment and decrease the accessibility of correcting for such overassessment to avoid delinquency and foreclosure.

Largely left unanswered is whether overassessment as an unexpected deviation from true market value amplifies the shock effect that results in household delinquency and foreclosure. In the only known study linking overassessment to subsequent tax foreclosure, Atuahene & Berry (2019) find 10% of Detroit's tax foreclosed properties are also overassessed (p. 7), and the risk of both is higher for Black residents. In Philadelphia, Fu (2022) is the only study examining the relationship of property tax increases to delinquency, but does not narrow to increases to overassessments, does not extend the analysis to foreclosure, and narrows to single family homes only. She reports a "$100 increase in property taxes raises property tax delinquency by 3.9% after one year and 7.7% after two years" (Fu, 2022, p.1). Fu (2022) found it to be "easier for White owners to recover from delinquency, while some mechanism is making it more difficult for Black owners to recover" (Fu, 2022, p. 23). This study's regression border discontinuity design shows that the price elasticity of delinquency is, as expected, higher for Black rather than White residents. Even after the 2013 AVI, Black residents experience a "persistent rise of delinquencies", of which snowball across time (Fu, 2022, p. 23). Mounting interest and fees may spur repeat delinquencies that may increase foreclosure risk, as the process can take up to seven years in Philadelphia.

2.4 Spatial Spillovers

An offshoot of property tax research focuses on delinquency and foreclosure spatial spillovers. When assessment increases (for individual properties or on a neighbourhood level) spur tax foreclosure, this may risk negative spatial externalities by dampening neighbouring market values and initiating blight. Most studies connect foreclosure with general assessment increases rather than overassessment, but regression results for Indianapolis in Payton (2014) show that a higher concentration of tax foreclosures in a neighbourhood then simultaneously reduces sales values and increases overassessments of nearby properties (p.19). Over time, spillovers of depressed market values risk circularity with overassessment, so "the fairness in tax burden in urban areas, on a neighbourhood-by-neighbourhood basis, may be affected substantially as a result of higher concentrations of foreclosures" (Payton, 2014, p. 19). What remains unstudied is overassessment's relationship to subsequent tax foreclosures.

A study of Chicago reinforces these findings on delinquency and foreclosure spillovers across time in what Alm et. al (2016) term the "delinquency discount". This means that a delinquent property corresponds to a reduction in sales values of properties within the same Census Block of 2.5% and of 5% for a tax foreclosed property, then corresponding to further delinquencies in the area (Alm et. al, 2016, p. 8). Gillen (2013) apply the delinquency discount to Philadelphia, estimating the reduction in sales price for a property that neighbours a delinquent or foreclosed property to be modest at 1% (p. 9). This discourse on spatial contagion perhaps explains why delinquency and foreclosure exhibit neighbourhood as well as household-level variation.

2.5 Assessment Model Transitions

This section briefly reviews the development of promising error-reducing models and the opportunities and barriers for their implementation. Concerns surrounding bias and error date back to the property tax's inception, meaning discrimination has evolved with assessment methods (Kahrl, 2013). Rapid growth in the stock of single family homes in the mid twentieth century led U.S. cities to pursue MLR out of a need for economies of scale (McCluskey & Adair, 1997, pp. 257, 258). Early in MLR's application Black taxpayers nationwide lost an estimated 6.5 million acres of overassessed land (Kahrl, 2013, p. 38). In the late 1970s U.S. municipalities increasingly procured commercial CAMA systems with MLR integral to their technology. U.S. Congress simultaneously passed stricter ethics and CAMA design standards (Wang & Li, 2019, p. 2), enforced by the International Association for Assessing Offiers (IAAO). Academia responded by offering a number of alternatives including Geographic Information System (GIS) allowing for locational value characteristics (McCluskey et. al, 2013, p. 21). Automated Valuation Models (AVMs) were also proposed to fully automate the variable selection process (RICS, 2022, p. 16). A subset of AVMs, Artificial Neural Networks (ANNs) emerged as the academically favoured Artificial Intelligence (AI) based alternative in the 1990s, though application is limited. Currently, heightened awareness of the MLR 'black box' and overassessment nationwide is accelerating litigation with rulings favoring households. By providing evidence of systematic overassessment these rulings mandate costly CAMA changes and tax refunds.

Assessment reform fervour mounted as housing costs rose in Philadelphia at the start of the 21st century (Philadelphia Forward, 2003). CAMA was first tested on the citywide level in response to advocacy, decades after most U.S. cities (Dowdall & Warner, 2012, p. 12). Punctuating this period of assessment reform, OPA pursued the AVI in 2013. This sweeping package was Philadelphia's full-scale implementation of CAMA and introduction of the current MLR model. This model improved accuracy only for single family homes outside of the lowest-income zones (IAAO 2022; Hincken, 2022). In 2020 OPA implemented the popular cloud-based iasWorld CAMA System from Tyler Technologies. OPA maintains the same MLR model despite iasWorld's flexibility for a range of alternatives (Gloudemans, 2019, p. 4). Most recently the Philadelphia Residential Property Assessment Task Force was created to address racial and ethnic assessment bias (OPA, 2024). There thus exists a political and technical window of opportunity for further reform despite Philadelphia history of lagged technological adoption.

2.6 Conceptual Framework and Theoretical Hypotheses

The research gaps are the increment from the theoretical and empirical foundation to the research (sub)question, motivated by the social problem presented in Section 1.2.1. Shown in Figure 1, these gaps are in connecting the given characteristics with overassessment in Philadelphia, and in connecting overassessment to delinquency and foreclosure risk in general. Random effects as well as time and entity fixed effects are included as controls predicated in the literature. The four theoretical hypotheses below are formulated to test these relationships. Also explored is overassessment's relationship to structural and locational characteristics when testing hypotheses one and two for the demographic characteristics of primary concern. Similarly, demographics in relation to delinquency and foreclosure are explored while testing hypotheses three and four.

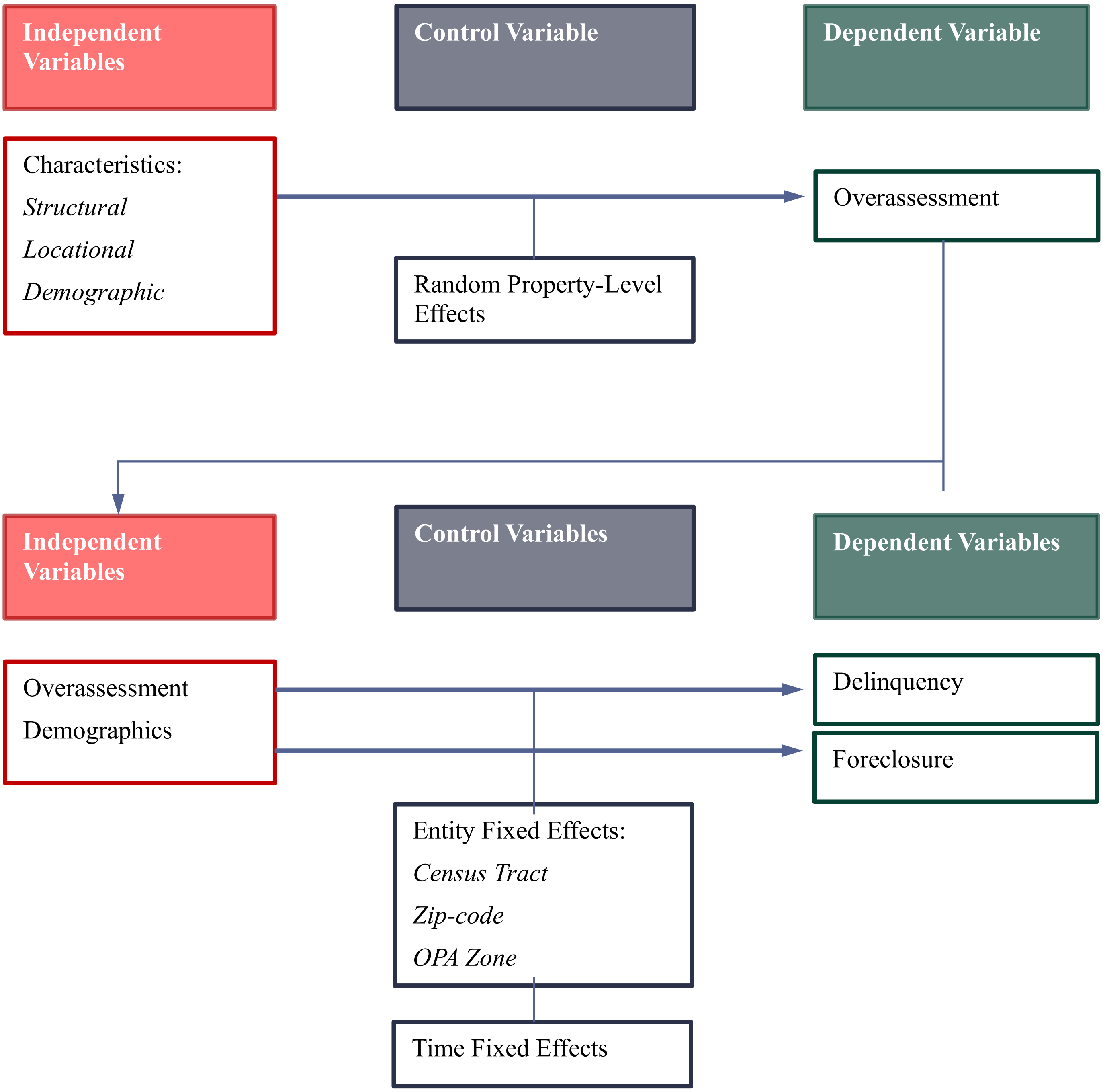
H1: Overassessment has a positive association with racial and ethnic minority share.

H2: Overassessment has a negative association with income level.

H3: Overassessment has a positive association with the probability of delinquency.

H4: Overassessment has a positive association with the probability of tax foreclosure.

Figure 1: Conceptual Framework



3. Research design, methodology

3.1 Description of research design and methods

The empirical strategy fulfils two objectives in order to answer the research (sub)question. First, to identify the share of overassessment accounted for by OPA's model specification versus the share due to random variation. This is done by identifying factors associated with overassessment and controlling for random error. The second objective is to test if overassessment carries through to an increased likelihood of tax delinquency and foreclosure, and what related factors increase their likelihood. Separate panel regression models are run estimating predictors of overassessment, delinquency, and foreclosure.

First, the panel data technique of random effects regression is used to distinguish between systematic overassessment variation across measurable variables and random overassessment variation. This panel data technique is appropriate "if the individual-specific component μi is uncorrelated with the regressors…the overall error uit also is, so the OLS estimator is consistent" (Croissant & Millo, 2008, p. 3). Here, random effects control for unspecifiable and random heterogeneity between properties, arising from manual mistakes in the assessment process (Berry, 2021). In other words, to isolate associations with variables that are actionable for process reform, random noise in individual overassessments is specified akin to Allen & Dare (2002), Bidanset et. al (2019), and Chun & Linneman (1985).

Next, entity fixed effects regression for panel data is used to test overassessment's relationship with delinquency and foreclosure. Entity fixed effects are difficult to measure, time-invariant, and entity variant. Possible fixed effects include procrastination (Chirico et.al, 2019) and ideology (Bahl et. al, 2010) on the property level and within-neighbourhood spillovers addressed in Section 2.4 on the neighbourhood level. Such fixed effects are controlled for as this study is chiefly concerned with isolating overassessments' relationship to delinquency. Fixed effects on delinquency and foreclosure at multiple geographical levels are tested here as performed in Atuahene & Berry (2018) for the zip-code level, Payton (2014) and Alm et. al (2018) for Census block level, and Payton (2014) for the sub-jurisdictional level.

Lastly, time fixed effects are considered due to expected temporal variation due to fluctuations in real estate market and economic conditions. Time fixed effects are entity invariant omitted variables that vary across time. For delinquency and foreclosure these effects aim to capture broad market value increases in the previous decade (Federal Housing Finance Agency, 2024, p. 5; Guzman & Kollar, 2023, p. 49). Year fixed effects methods allow for more accurate estimates of the association with overassessment, as is the case for Fu (2022) for delinquency and Atuahene & Berry (2019) for overassessment and foreclosure.

3.2 Data sources, operationalisation, and expectations

3.2.1 Data Sources and operationalisation

Analysis is run on an unbalanced micro-panel of 399,000 properties over nine years (2015-2024); the entire population of residential non-vacant properties except those in zones G and H. OPA's model remains constant throughout the period. Property-level variables are available through OPA 's public datasets. These include residence type, style, delinquency, and foreclosure status as listed in the operationalisation of concepts in Table 2. Census tract-level variables for racial and ethnic minorities and income are available for each property. The U.S. Census Bureau American Community Survey measures each tract's population share by race and ethnicity. These are annual estimates for 2015-2019 and 2021-2024, whereas for 2020 they are population data. Ethnicity is measured as either Hispanic or non-Hispanic, and race categories include White, Asian, Pacific Islander, Native American, Black. The ethnicity category of Hispanic and race categories White, Asian, and Black are included. Asian includes individuals with origins in South Asia, East Asia, and Southeast Asia. Median household income is similarly provided by tract.

Table 2: Operationalisation

Concept	Description	Variable	Measurement	Data Sources
Overassessment	Percentage point increase of a property's assessment to sales ratio above its zonal median ratio.	Y_1: Overassessment (*ln*)	Continuous within $[0,\infty)$	OPA's Property Assessment History
Delinquency	Non-payment of the property tax bill within one year	Y_2: Delinquent	1: Delinquent 0: Current	DoR's Real Estate Tax Delinquencies
Tax Foreclosure	Claim placed on property title. Property is up for auction or has been sold.	Y_3: Foreclosed	1: Foreclosed 0: Not Foreclosed	DoR's Real Estate Tax Delinquencies
Structural Characteristics	Aggregate property style categories as indicated by visible structural characteristics.	D_1: Semi-Detached D_2: Row D_3: Apartment D_4: Condo D_5: Mixed	For example, 1: Semi-Detached 0: Detached	OPA's Property Assessment History
Zoning Designation	Aggregate property type categories as by zoning	D_6: Multifamily D_7: Apartments D_8: Mixed Use	For example, 1: Multifamily 0: Single family	OPA's Property Assessment History

	designation which indicates density and legal ownership.			
Minority Population	Percentage of racial and ethnic minorities out of the total population of the property's Census Tract.	X_1: Black Percentage X_2: Hispanic Percentage X_3: Asian Percentage	Continuous within [0,100]	U.S. Census American Community Survey
Income Level	Property's Census Tract's median household income in USD, measured as a percentage point decrease.	X_4: Negative Log of Median Income	Continuous within $[0,\infty)$	U.S. Census American Community Survey

3.2.2 Random Effects

The linear random effects model equation takes the following form:

$$(2)\ \text{OVER}_{i,t} = \alpha + ln\text{INC}_{c,t} + \text{MIN}_{c,t} + \text{STYLE}_{i,t} + \text{TYPE}_{i,t} + u_{i,t} + \varepsilon_{i,t}$$

Where for each property *i*'s census tract *c* in year *t*, the independent variable $ln\text{INC}_{c,t}$ measures the log of a decrease in median income level and $\text{MIN}_{c,t}$ shows racial and ethnic minority population share. $\text{STYLE}_{i,t}$ represents property *i*'s aggregate structural characteristics and $\text{TYPE}_{i,t}$ its zoning designation in year *t*, both indicated by dummy variables in Table 2. While these two property-level variables are measured across *t*, they have minimal temporal variation. The between-entity error term $u_{i,t}$ controls for the entity-specific unspecifiable heterogeneity for each year *t* in the panel dataset, while the within-entity error $\varepsilon_{i,t}$ does so for the remaining residual.

3.2.2.1 Dependent Variable: Overassessment

Overassessment is calculated as such:

$$(3)\ \text{OVER}_{i,t} = \ln\left[\frac{(\text{A/S})_{i,t}}{(\text{A/S})_{z,t}}\right]$$

Where $OVER_{i,t}$ is the natural logarithm of the positive difference between property *i*'s assessment to sales ratio (A/S) in year to its OPA zone *z*'s median A/S in year *t*. As variable Y_1 in Table 2, taking the natural logarithm of this difference shows how many percentage points property *i*'s assessment takes above the median assessment of properties with the most similar market values and charactieristics.

Overassessment's operationalisation is based in public finance literature on HI, meaning that "properties with similar market value are treated uniformly and appraised at the same percentage of market value" (Bidanset et.al, 2019, p. 3). It is measured in both academic studies and industry audits through A/S (Allen & Dare, 2002). Being taken before the rate, exemptions, credits, and deductions are applied it allows for analysis of valuation model errors unobstructed by post-assessment policy (Avenancio-Leon & Howard, 2022). A/S difference above the zonal median is in line with the overassessment operationalisation used by Chun & Linneman (1985) and Berry & Bednarz (1975).

3.2.2.2 Independent Variable: Median Income

Income level is measured as median income for a property *i*'s Census tract. Tract as a proxy for the neighbourhood level follows conventional operationalisation in the econometric literature for income including Avenancio-Leon & Howard (2022), Amornsiripanitch (2024), and Allen & Dare (2002). Although minority population and median income are not available on the property level, the Census Bureau draws tracts based on homogeneity "with respect to population characteristics, economic status, and living conditions" (U.S. Census, 2023). Median income and minority population for each tract are thus assumed to be representative of the average property within the neighbourhood. The expected relationship to overassessment is derived from findings on accuracy. Higher HI in Philadelphia is exhibited in lower median income neighbourhoods (Hou et. al, 2023, p. 16) and zones (Strauss & Hou, 2013, p. 40).

3.2.2.3 Independent Variable: Minority Population

Following econometric studies on HI, delinquency, and foreclosure, minority population is measured as racial and ethnic minorities' proportion of the population in the Census tract wherein the property is located (Weber & McMillen, 2010; Fu, 2022; Berry, 202; Avenancio-Leon & Howard, 2022; Alm et. al, 2016). As of 2020, Black, Hispanic, and Asian are the three largest racial and ethnic minority categories in Philadelphia, standing at approximately 44%, 15%, and 8% respectively. Before OPA's current model, Strauss & Hou (2013) find majority Black neighbourhoods to be overassessed on average. Under the current model, Hou et. al (2023) find general assessment inaccuracy to be more frequent and larger for non-White neighbourhoods (p. 17). Similar results for overassessment under the current model are expected. Expectations for the Asian category are not clear from the outstanding literature, and sorting across properties and neighbourhoods is not well-established as for Black and Hispanic categories.

3.2.2.4 Independent Variable: Residence Style

Structural characteristics are frequently aggregated by property style in studies such as Hou et. al (2023) and Sirmans et. al (2008). OPA measures styles by six main aggregate categories that are the most structurally homogeneous. Literature finds average overassessment increases with omitted property characteristics such the number of units (Cornia & Slade, 2005, p. 37). Although OPA's model specifies style, styles with higher levels of these omitted structural characteristics are expected to have larger estimates.

3.2.2.5 Independent Variable: Residence Type

Residence type refers to property *i*'s zoning designation, which is selected as the most succinct neighbourhood feature. Used here is OPA's categorisation of residence types by 'Single family', 'Multifamily', 'Apartments above 4 units', and 'Mixed Use'. These are distinct along two dimensions of zoning designation being legal ownership and density. Single family has low density, multifamily has moderate density, and apartments, and mixed use have moderate to high density (Philadelphia City Planning Commission, 2022). Multifamily is found to be consistently less accurate (though not necessarily overassessed) than Single family in Philadelphia, but apartments and mixed use have not yet been examined (IAAO, 2022). Expected is a similar result as Smith's (2008), being a 12.5% average decrease in overassessment for single family (medium density) zones over non-single family (high density) zones (p. 13).

3.2.3 Delinquency and Fixed Effects

The time and entity fixed effects logit equation for delinquency is as follows:

$$(4)\ \mathrm{DELINQ}_{i,t} = \alpha + ln\mathrm{INC}_{c,t} + \mathrm{MIN}_{c,t} + \mathrm{OVER}_{i,t-1} + \delta_z + \gamma_t + \mu_{i,z,c,t}$$

Where dependent variable $\mathrm{DELINQ}_{i,t}$, Y_2 in Table 2, denotes whether a property *i* is recorded as delinquent in year *t*. The independent variables $ln\mathrm{INC}_{c,t}$ and $\mathrm{MIN}_{c,t}$ are as described in Section 3.2.2. and Table 2. $\mathrm{OVER}_{i,t-1}$ is specified with a one-year lag. The fixed effects term δ_z creates an intercept for each OPA zone *z*, while the term γ_t does so for each year.

3.2.3.1 Dependent Variable: Delinquency

Philadelphia property tax bills are received January 1 and due March 31, after which interest and late penalties accrue until the following December 31, being when the taxpayer is recorded as delinquent (Chirico et.al, 2016, p. 30). DoR data on the household level show each year a new delinquency is recorded for a property. Assessment dates thus have a delinquency date with a one-year lag.

3.2.3.2 Independent Variables: Median Income and Minority Population

Following Hayashi (2020), it is anticipated that properties in tracts with lower median incomes will have higher delinquency probabilities. Similarly, Carroll & Goodman (2017) establish a significant association with delinquency testing median income and minority population specifically on the neighbourhood-level. Despite its status as the most impoverished large city in the U.S., Philadelphia's population that falls below federal poverty income threshold has slightly declined from 26% in 2015 to 22% in 2022 (U.S. Census Bureau, 2024). The decreasing poverty rate may contribute to an increased financial capacity to avoid delinquency for these lower-income households across the period.

3.2.3.3 Independent Variable: One Year Lagged Overassessment

It is expected that an overassessed property *i* in year *t-1* has a higher likelihood of delinquency in year *t*. I anticipate these odds to be slightly larger than Fu (2002) who finds an associated 3.9% increase in delinquency odds for a 1% point increase in overall assessment (p. 16).

3.2.4 Foreclosure and Fixed Effects

The time and entity fixed effects logit equation for foreclosure is as follows:

$$(5)\ \text{FORECL}_{i,t} = \alpha + ln\text{INC}_{c,t} + \text{MIN}_{c,t} + \sum_{i=3}^{j=6} \text{OVER}_{i,t-j} + \delta_z + \gamma_t + \mu_{i,z,c,t}$$

Where $\text{FORECL}_{i,t}$, as dependent variable Y_3 in Table 2, shows whether a property *i* has been foreclosed in year *t*. Here overassessment is specified with lags from 3 to 6 years in $\text{OVER}_{i,t-j}$. Terms $ln\text{INC}_{c,t}$ and $\text{MIN}_{c,t}$, and fixed effects δ_z and γ_t are as mentioned in Section 3.2.3.

3.2.4.1 Dependent Variable: Tax Foreclosure

Prolonged delinquent properties can reach a public auction known in Philadelphia as a "sheriff's sale". Delinquent properties that are both actionable for auction and those that have been sold are considered to have reached tax foreclosure and Y_3 takes a value of 1.

3.2.4.2 Independent Variable: Multiple Years Lagged Overassessment

In Philadelphia a delinquent property can take between 2 to 5 years before reaching foreclosure, so the association with overassessment is lagged between 3 and 6 years. Literature on foreclosure behavior and overassessment is sparse, so expectations are based on results in Detroit where a 1 unit increase in overassessment increases foreclosure probability by 2% points (Atuahene & Berry, 2019). Theoretical expectations for $ln\text{INC}_{c,t}$ and $\text{MIN}_{c,t}$ match Section 3.2.3.2, as both tax foreclosure and delinquency are understood as a metric of financial distress that vary across neighbourhood demographic composition.

3.2.5 Adjustments

First, the full set of 2015-2023 assessment values for all properties is created by matching properties' parcel identifiers across annual datasets. To obtain the A/S difference, the City Controller's procedure for auditing OPA's assessment values is replicated. Audit calculations for the entire set of residential properties from 2015-2023. Calculating the industry standard A/S difference requires four steps (IAAO, 2022, p. 41). First it takes the assessment to sales ratio for each property, then secondly uses these to calculate the jurisdictional (zonal) median ratio. Thirdly, within each zone, it adjusts for OPA's physical characteristics then lastly takes the difference of each property's A/S to its zonal median.

OPA provides each property's Census tract, so properties' tract-level data is input by matching OPA's tract for each property to the Census Bureau datasets. For 2015-2019, the 2010 Census tracts are used and the 2020 tracts for 2020-2024. The Census classifies Hispanic as an ethnic group, and thus the category Hispanic other-race will also be included, and White is omitted as the reference categorical variable. Parcel identifiers are used to match properties' in the DoR delinquency and foreclosure records with their OPA assessment data.

3.2.6 Expected challenges and limitations

Random effects models bear the assumption that all entity fixed effects have been specified in order for the error term to be uncorrelated with the covariates. Literature points to additional property-level variables related to overassessment not tested here, for instance green space access and criminal activity found significant by Huang et. al (2010), so the specified variables may be correlated with the random effects residual.

Another limitation is the differing scales across variables, specifically measurement at the tract level for minority population share and income, and at the property level otherwise. Legal constraints for disclosure of household-level Census data make this lack of precision an endemic limitation for overassessment, delinquency, and foreclosure studies. Mismatch scenarios such as a 'White' household may be located in a majority 'Asian' tract may occur. Revealing any assessor bias targeted at individual household income and minority status is thus not feasible. However, as noted, tract is often utilised as a neighborhood proxy and there is evidence of neighbourhood-level overassessment. What can be revealed is assessor bias for neighbourhoods of different income levels and minority populations. If a White household lives in a majority Black tract, they may still experience a higher level of overassessment similar to Black households in the tract.

The primarily limitation is that OPA is missing data on all properties located in zones G and H, which audits by IAAO (2022) and Ryan (2018) report are the most overassessed zones. There is thus a highly understated quantity of overassessed properties, and expected underestimated relationship with delinquency and foreclosure. The data are complete for all other zones.

4. Results, analysis, and discussion

4.1 Descriptive Statistics

Table 3 reports the minimum, maximum, standard deviation, and average for the variables of interest. The average property is overassessed by 18%, outside the IAAO standard maximum of 10% (IAAO, 2017, p. 10). 8% of all residential properties are recorded as delinquent in any year from 2015-2023, and out of these .4% reach foreclosure by 2023. Not considering the delinquency date, conditional means show that 7.6% of overassessed properties have a delinquency record compared to 8% for non-overassessed properties. Row properties represent 75% of residential properties, and 89% are in single family (low density) districts.

Table 3: Summary Statistics

	Min	Max	Std. Dev	Mean
Overassessment	0	1	0.28	0.18
Delinquent	0	1	0.27	0.08
Foreclosed	0	1	0.06	0.004
Demographics				
Median Income	9276.05	172610.60	23421.25	48631.40
Black Percentage	0	99.80	34.98	42.10
Hispanic Percentage	0	90.25	18.64	14.51
Asian Percentage	0	65.20	7.04	6.49
Property Style				
Detached	0	1	0.26	0.07
Semi Detached	0	1	0.37	0.17
Row	0	1	0.43	0.75
Apartment	0	1	0.05	0
Condo	0	1	0.04	0
Mixed	0	1	0.04	0
Property Type				
Single family	0	1	0.31	0.89
Multifamily	0	1	0.26	0.07
Mixed Use	0	1	0.16	0.03
Apartments	0	1	0.06	0

4.2 Interpretation of Results

4.2.1 Overassessment

Each model specification is run using both least squares estimation and best linear unbiased prediction, with the former producing a single residual term and the latter producing random errors for each property (Robinson, 1991). Random effects in Table 4, Model 5 yielded a lower adjusted R2 than the MLR models 1 through 4, though all hovering extremely low. The covariates thus explain more of of overassessment's variability without unobservable random effects between properties.

Table 4: Multiple Least Squares Regression Estimates on Overassessment

Dependent Variable: Overassessment (ln)

	(1)	(2)	(3)	(4)	(5)
Demographics					
Median Income (ln)	0.466***	0.503***	0.713***	0.476***	-0.628***
	(0.007)	(0.007)	(0.002)	(0.007)	(0.020)
Black Percentage	0.0002**	0.004***	0.008***	0.001***	0.008**
	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0002)
Hispanic Percentage	0.009***	0.006***	0.014***	0.009***	0.014***
	(0.0002)	(0.0004)	(0.0004)	(0.0002)	(0.0004)
Asian Percentage	0.015***	-0.012***	-0.008***	0.014***	-0.008***
	(0.0003)	(0.001)	(0.001)	(0.0004)	(0.001)
Property Style: Single Detached Base					
Semi Detached	0.146***	0.073***	10.477***	0.101***	9.581***
	(0.009)	(0.010)	(0.264)	(0.009)	(0.246)
Row	0.767***	0.583***	16.121***	0.776***	15.182***
	(0.008)	(0.014)	(0.258)	(0.009)	(0.237)
Apartment	- 0.356***	-.0366***	-4.920***	-0.656***	-.0270***
	(0.034)	(0.034)	(0.520)	(0.035)	(0.034)
Condo	0.317***	0.331***	1.888	0.321***	-2.801**

	(0.044)	(0.044)	(1.306)	(0.044)	(1.302)
Mixed	-1.679***	-1.818***	-4.378**	-1.208***	-1.545***
	(0.060)	(0.060)	(1.956)	(0.072)	(0.061)
Property Type: Single Family Base					
Multifamily	2.487***	2.473***	2.485***	2.745***	2.484***
	(0.008)	(0.008)	(0.008)	(0.025)	(0.008)
Mixed Use	0.326***	0.302***	0.304***	1.114***	0.304***
	(0.013)	(0.013)	(0.024)	(0.052)	(0.013)
Apartments	1.705***	1.664***	1.774***	1.980***	1.840***
	(0.044)	(0.044)	(0.044)	(0.045)	(0.0440
Interaction Terms					
Black: Row		-.005***	-0.011***		--0.011***
		(0.0002)	(0.0002)		(0.0002)
Hispanic: Row		0.022***	-0.009***		-0.008***
		(0.0004)	(0.0005)		(0.0005)
Asian: Row		0.037***	0.031***		0.031***
		(0.001)	(0.001)		(0.001)
Neg Median Income (ln): Semi			.945***		.863***
			(0.024)		(0.022)
Neg Median Income (ln): Row			1.386***		1.301***
			(0.045)		(0.021)
Neg Median Income (ln): Apartment			0.475***		
			(0.048)		
Neg Median Income (ln): Condo			-.0175		-0.258**
			(0.116)		(0.116)
Neg Median Income(ln): Mixed			-0.270		
			(0.024)		
Black: Multi				-.002***	
				(0.0002)	
Hispanic: Multi				0.021***	

				(0.001)	
Asian: Multi				-0.004***	
				(0.001)	
Black: Mixed Use				-0.016***	
				(0.0004)	
Hispanic:Mixed Use				-0.028***	
				(0.001)	
Asian: Mixed Use				0.004**	
				(0.002)	
Constant	-1.510***	-0.923***	-13.597***	-1.413***	-1.420***
	(0.075)	(0.075)	(0.244)	(0.075)	(0.222)
Observations	3,593,313	3,593,313	3,593,313	3,593,313	3,593,313
Adjusted R2	0.037	0.039	0.040	0.039	0.040
Resid Std. Errror	3.938	3.935	3.933	3.935	3.930
Random Effects	No	No	No	No	Yes
Note:	Standard errors in parentheses. *p<0.10, **p<0.05, ***p<0.01				

4.2.1.1 Independent Variables

Taking Model 1 in Table 4 as a base of comparison, a row home is overassessed by 115% more than a single detached home on average, a condo by 37.3%, and a semi-detached home by 15.7%. These coefficients are intuitively positive. Apartments are overassessed by 30% less than single detached homes on average, which is unintuitive given Cornia & Slade's (2005) result that overassessment is associated with a higher number of units. Also unexpected is the negative association of 81.2% for homes in mixed-use buildings. It is expected that these buildings' heterogeneous omitted characteristics would associate with higher overassessment as found in Amornsiripanitch (2024). Every style and type coefficient is significant at the 1% level in Model 1. For property type, when a property is located in a multifamily zone rather than a single family zone the associated increase in overassessment is implausibly high at 1103%, and also for apartment zoned properties at 450%. Compared to single family, properties in mixed-use zones have have 38.6% greater average overassessment. While all expectedly positive, these relationships are greater in magnitude than found in Smith (2008). They also do not increase with density as moderate density multifamily's estimate is greater than the higher density districts of apartment and mixed-use.

Median income, tract percentage of Black population, and tract percentage of Hispanic population all meet directional expectations. For two identical properties with all else equal, the property in a tract with a median income of 1% lower is, on average, overassessed by

.46% more. Across all models, racial and ethnic minorities have smaller magnitudes than expected from Avenancio-Leon & Howard (2022)'s results of 13% higher average overassessment for neighbourhood Black population and 10% for Hispanic population (pp. 2, 29). Here, a one percentage point increase in a property's tract Black population is associated with an overassessment increase of only .02%, and by .9% for tract Hispanic population. Interestingly, the relationship with the Asian race category in the Model 1 is positive, with a one percentage point increase in a property's tract Asian population is associated with an overassessment increase of 1.5%. The White category is omitted due to high negative correlation and multicollinearity with the Black and Hispanic categories.

4.2.1.2 Interaction Terms

Relationships between race, ethnicity and style on overassessment are the most compelling interactions from theoretical expectations. While I do not test hypotheses on demographic sorting, high Pearson's correlation coefficients between variables indicate a degree of sorting that may increase the risk of overassessment when these variables are co-present. Tract White and Asian population shares are found to be 26% positively correlated with each other, suggesting a level of sorting into the same tracts. For reference, tract White population share is negatively correlated with Black population share by 82%, and negatively by 21% for Hispanic population share. As expected, White share has the highest positive and negative correlations with property styles, being 21% correlated with single detached homes and 26% negatively with row homes. Asian share bears a similar correlation with single detached and row homes as White groups. On the other hand, Black share has the inverse correlation, being 18% positively correlated with row homes and 16% negatively correlated with single detached. Hispanic share bears a similar positive correlation with row homes. Median income has a similar positive correlation with single detached homes as White population at 20% and a similar negative correlation with row homes at 19%. These correlations may suggest Black, Hispanic, and lower-income populations sort into row homes and White, Asian, and higher-income populations into single detached homes.

First, Model 2's interaction terms are all significant at the 1% level. A a row property in a tract with a Black population of 51% is on average overassessed by .5% less than a single detached property in a tract with a Black population of 50%. This is surprising given that both base terms have consistent positive association. The coefficient for Black population exhibits downward bias and thus increases when moving from Model 1 to Model 2. A row property in a tract with an Asian population of 51% is on average overassessed by 3.7% more than a single detached property in a tract with an Asian population of 50%. This result is interesting given that Asian population share is negatively correlated with Row properties. Upward bias in Model 1's Asian share term shows that once interacted with Row in Model 2, a 1% point increase in tract Asian population relates to a 1.2% decrease in overassessment compared to an increase in Model 1. Asian population alone does not correspond to an overassessment increase unless the property is a row home.

Model 3 examines any additional change in overassessment for those that sort into styles by tract median income level. For a row property, a decrease in tract median income of 1% corresponds to a 1.38% higher overassessment compared to a 1% median income decrease for a single detached property. These estimates are .96% for semi-detached and .47% for apartments, all significant at 1%. By accounting for these interactions, estimates for non-interacted semi-detached and row homes increase drastically, but decrease for apartments. The differing relationship of these styles to overassessment based on the tract income level cannot be explained by income-based sorting into lower valued properties within or between styles because market values are already held constant in the calculation of the A/S difference. Model 3 sees the highest adjusted R2, but still only 4% of the variation in overassessment is described by the covariates' variation.

Finally, interactions are considered here to determine if overassessment varies across certain combinations of racial and ethnic population shares and zoning designation. There is minimal correlation between minority groups and zoning designation so high levels of sorting by this neighbourhood feature is not expected despite Avenancio-Leon & Howard's (2022) findings on such. Significant at the 1% level, a property in a multifamily zoned district with a Black population of 51% is on average overassessed by .2% less than a property in a single family zoned district with a Black population of 50%. Similar to Black population and row homes in Model 2, Black population and multifamily districts are more intuitively described by the non-interacted terms in Model 3. For properties in multifamily rather than single family districts, a 1% point increase in tract Hispanic population corresponds to a 2.1% higher increase in overassessment. For properties located in both higher percentage Hispanic tracts in multifamily districts, there is an additional overassessment risk not encapsulated by the positive coefficients for Hispanic and multifamily alone.

4.2.2 Delinquency

4.2.2.1 Independent Variables

In Table 5, Model 1, a 1% decrease in a property's tract median income level intuitively increases the odds of delinquency by .73%. Results for racial and ethnic minorities resemble their directional relationships to overassessment, and are similarly lower than expected. A 1% point increase in a property's tract Black population corresponds to an increase in delinquency odds by 1.4% on average, and by .8% for a 1% point increase in Hispanic population, both significant at the 1% level. For comparison, by imputing homeowner race and ethnicity Fu (2022) reports these odds to be 2.65% for Black homeowners but with mixed significance across years (pp. 25, 26). Odds of delinquency decrease by 2.8% for a marginal increase in Asian population. Model 1 also estimates a 1% increase in overassessment decreases the odds of delinquency by .002% in the following year.

Table 5: Logit Regression Estimates on Delinquency

Dependent Variable: Delinquent

	(1)	(2)	(3)	(4)
Overassessment (ln): Lag 1	-0.002***	0.037**	0.004	0.0153
	(0.0005)	(0.0123)	(0.0004)	(0.0120)
Demographics				
Neg Median Income (ln)	0.725***	0.747***	0.878***	0.434***
	(0.0060)	(0.0093)	(0.0095)	(0.0223)
Black Percentage	0.014***	0.014***	0.0121***	0.071***
	(0.0001)	(0.0001)	(0.0001)	(0.0025)
Hispanic Percentage	0.008***	0.008***	0.006***	0.140***
	(0.0001)	(0.0001)	(0.0001)	(0.0034)
Asian Percentage	-0.028***	-0.028***	-0.029***	-0.176***
	(0.0004)	(0.0000)	(0.0004)	(0.0119)
Zone Fixed Effects: Zone A Base				
Zone B	-0.509*	-0.510*	-0.516*	-0.594
	(0.2171)	(0.2171)	(0.2171)	(0.2167)
Zone C	0.360**	0.359**	0.362**	0.308*
	(0.1359)	(0.1359)	(0.1362)	(0.1355)
Zone D	0.738***	0.738***	0.764***	0.811***
	(0.1111)	(0.1111)	(0.1111)	(0.1113)
Zone E	0.051*	0.051*	0.055*	0.125***
	(0.0247)	(0.0247)	(0.0248)	(0.0248)
Zone F	0.200***	0.200***	0.1919***	0.208***
	(0.0122)	(0.0122)	(0.0122)	(0.0122)
Year Fixed Effects: 2015 Base				
2016			0.040***	0.034***
			(0.0007)	(0.0008)
2017			0.038***	0.024**
			(0.0012)	(0.0083)

2018			0.107***	0.099***
			(0.0023)	(0.0084)
2019			0.155***	0.151***
			(0.0020)	(0.0083)
2020			0.246***	0.241***
			(0.0046)	(0.0083)
2021			0.297***	0.294***
			(0.0047)	(0.0085)
2022			0.389***	0.391***
			(0.0072)	(0.0086)
Interaction Terms				
Neg Median Income (ln): Over (ln) Lag 1		0.004**	0.001	0.002**
		(0.0011)	(0.0032)	(0.0011)
Neg Median Income(ln): Black				0.005***
				(0.0003)
Neg Median Income(ln): Hispanic				0.013***
				(0.0004)
Neg Median Income(ln): Asian				-0.014***
				(0.0011)
Observations	3,593,313	3,593,313	3,593,313	3,593,313
Log Likelihood	-919,664,700	-919,664,700	-919,664,700	-919,664,700
Bayesian Inf. Crit.	1,836,069.200	1,839,500.500	1,836,069.200	1,833,659.300
Adj. Pseudo R2	0.073	0.073	0.075	0.0764
Note:	Standard errors in parentheses. *p<0.10, **p<0.05, ***p<0.01			

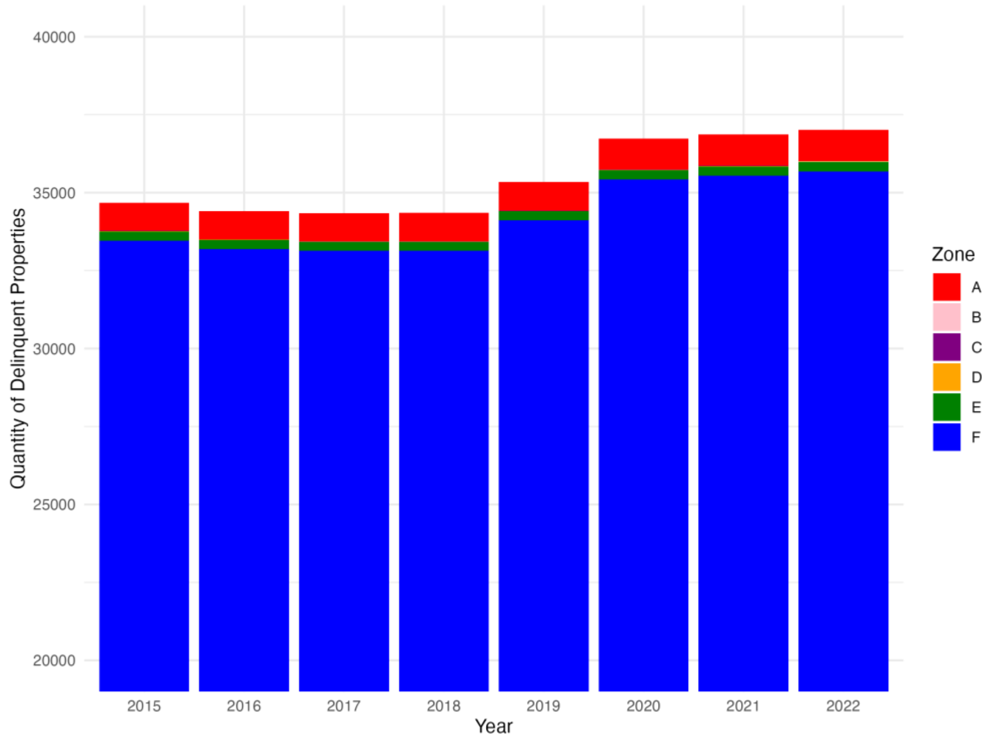
4.2.2.2 Interaction Terms

Once considered together with median income in Model 2, delinquency odds for overassessment become positive at .037% (significant at the 5% level), smaller than Fu's (2022) odds from general assessment increases. As tract median income decreases and the previous year's overassessment increases by 1%, delinquency odds increase by an additional .004% in addition to the increased odds from both negative income and overassessment alone. However, by specifying year fixed effects, Model 3's overassessment estimate and interaction with median income are not significant at any level. Model 4 sees the highest adjusted pseudo R2 by including interactions between income, race, and ethnicity, all significant at 1%. Median income's odds decrease to .43% when considering the interaction between tract median income and minority population in Model 4. The odds of delinquency given a 1% point increase in Asian population are still negative even when there is a 1% decrease in median income, but such a decrease given marginal increases in Black and Hispanic population compound delinquency odds.

4.2.2.3 Time and Zone Fixed Effects

Figure 2 displays incremental annual fluctuations in quantity of delinquent properties, showing the difference of new delinquents in year *t* and delinquents from previous years made current in year *t*. Unobservable heterogeneity across entities is also tested for property, tract, zip-code, and zone. Tract and zip-code intercepts are provided in Annexes 3 and 4, while property fixed effects were non-estimatable. Figure 2 supports this by showing that delinquencies vary by zone but between-zone variation is largely time constant. Zones A and F are outside the IAAO assessment accuracy standard and represent a disproportionate share of total delinquents; Zone F at 96.5%.

Figure 2: Total Quantity of Delinquent Properties by Year and Zone



Slight downward bias in median income is corrected for upon specification of year fixed effects in Model 3 which shows positive and increasing year fixed effects odds ratios, significant at the 1% level. Decreases in the citywide poverty rate from 2015 to 2022 do not relate to lower delinquency odds with unmeasured year effects instead displaying a steady increase in odds across this period. Fixed effects for Zones D and F are significant at 1%, with the probability of delinquency increasing by 109% if a property is located in D rather than A.

4.2.3 Foreclosure

4.2.3.1 Independent Variables and Interactions

Models 1 and 2 in Table 6 show marginal increases in a property's tract Hispanic and Black populations as well as overassessment have positive foreclosure odds ratios, and only overassessments with a 6 year lag are significant and thus reported. Model 2 reports a 1% decrease in a property's tract median income and 1% increase in its overassessed amount increases the odds of foreclosure by an additional .095%. However, neither minority share nor overassessment are significant at any level upon year fixed effects specification in Models 3 and 4, counter to findings on foreclosure odds and overassessment using year fixed effects in Atuahene & Berry (2019). Median income's odds ratios are also unexpectedly no longer significant at the acceptable 5% level.

Table 6: Logit Regression Estimates on Foreclosure

Dependent Variable: Foreclosed

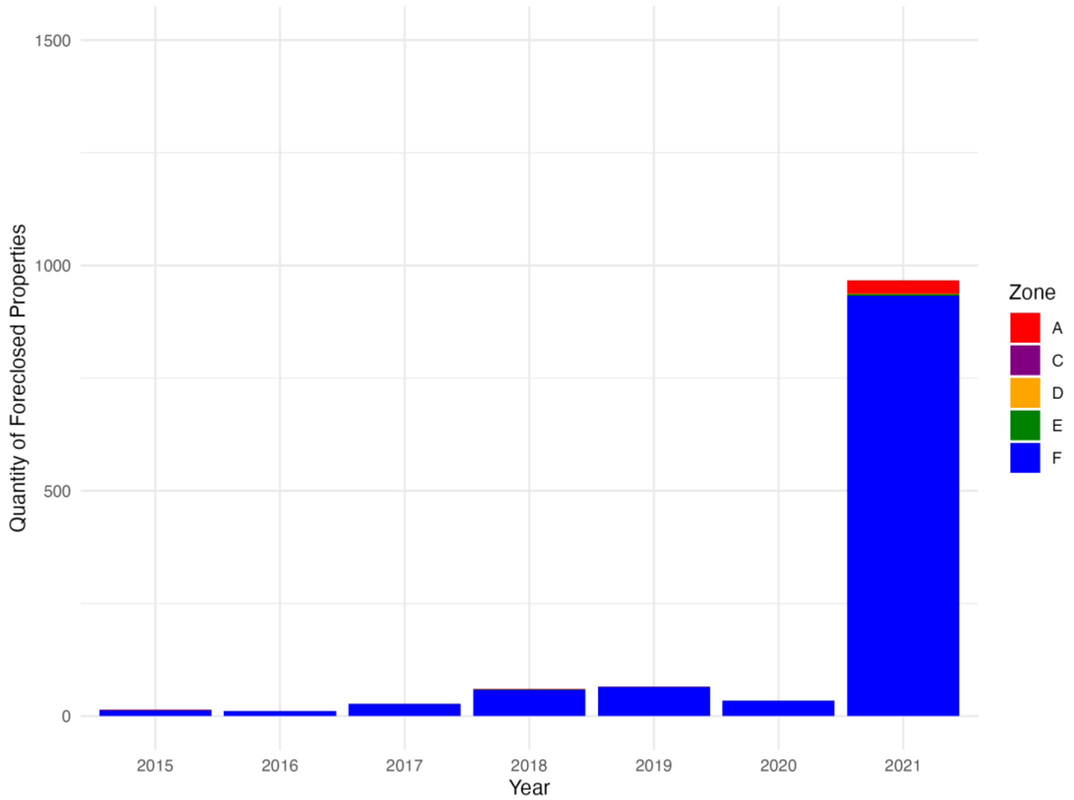
	(1)	(2)	(3)	(4)
Overassessment (ln): Lag 6	0.182***	1.185***	-0.098	-0.094
	(0.008)	(0.190)	(0.190)	(0.190)
Demographics				
Neg Median Income (ln)	-0.330***	0.288*	0.266*	0.268*
	(0.094)	(0.150)	(0.149)	(0.002)
Black Percentage	0.007***	0.008***	0.001	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Hispanic Percentage	0.009***	0.011***	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Asian Percentage	-0.011			
	(0.007)			
Year Fixed Effects: 2015 Base				
2016			-0.225	-0.225
			(0.403)	(0.403)
2017			0.667**	0.667**
			(0.329)	(0.329)
2018			1.516***	1.516***
			(0.297)	(0.297)
2019			1.587***	1.587***
			(0.295)	(0.295)
2020			0.916***	0.916***
			(0.318)	(0.318)
2021			4.240***	4.239***
			(0.272)	(0.272)
2022			-13.680	-13.680
			(151.620)	(151.583)
Zone Fixed Effects: Zone A Base				

Zone B				-15.707
				(5,522.423)
Zone C				1.407
				(1.060)
Zone D				0.889
				(1.046)
Zone E				-0.755
				(0.486)
Zone F				-0.099
				(0.187)
Interaction Terms				
Neg Median Income (ln): Over Lag 6		0.095***	-0.012	-0.011
		(0.018)	(0.018)	(0.018)
Observations	283,722	283,722	283,722	283,722
Log Likelihood	-7,391.991	-7,379.150	-6,096.186	-6,093.592
Bayesian Inf. Crit.	14,859.316	14,833.634	12,355.597	12,413.191
Adj. Pseudo R2	0.033	0.035	0.202	0.203
Note:	Standard errors in parentheses. *p<0.10, **p<0.05, ***p<0.01			

4.2.3.2 Time and Zone Fixed Effects

Like delinquency, Zones A and F hold a disproportionate share of tax foreclosed housing stock, at 96.7% and 2.6% shown by Figure 3. Foreclosure varies more drastically than delinquency across years, with 81% of the foreclosures from the period 2015-2022 occurring in 2021. Zone fixed effects are not significant at any level.

Figure 3: Total Quantity of Foreclosed Properties by Year and Zone



20% of the variation in foreclosure is explained by the covariates by including year fixed effects in Models 3 and 4 in Table 6, also seeing a lower BIC and greater relative likelihood. While the probability of delinquency steadily increased across the period, that of foreclosure fluctuates and peaks at 69.6% in 2021 compared to 2015.

4.3 Discussion

This discussion attends to the research (sub)questions by analysing the results, addressing limitations, and placing findings in the broader research context. Both research questions are listed below.

What factors are associated with residential property overassessment, and how is overassessment related to delinquency and tax foreclosure in Philadelphia?

First, a high level of random assessor errors in valuing individual properties are not evident as Chun & Linneman (1985) found for Philadelphia's previous valuation model. Out of all property-level variables, row homes are on average the most overassessed relative to single detached homes, followed by condos. Both condos and row homes in Philadelphia share physical characteristics including multiple adjoining walls and multiple stories. Although OPA's model specifies property style, these characteristics that vary within and between styles are omitted. Semi-detached homes are the most structurally adjacent to single detached homes. They both have street-facing entrances and similar building and lot size ratios, but semi-detached homes contain only one adjoining wall with another unit. These similarities may explain why they are associated with a lower-level of overassessment compared to single detached homes than condos and row homes. These findings also suggest that OPA's model tends to overassess as the number of contiguous units in the physical structure increases. In other words, OPA's style variable may be too general and its physical characteristics variables too calibrated towards capturing value in single detached homes. Incremental structural deviations from this style relate to incremental increases in average overassessment. This complements Cornia & Slade's (2005) conclusion that overassessment tends to increase alongside a property's number of units when such is omitted from the valuation model (p. 37). Apartments and mixed-use properties are found to have a lower average overassessment than single detached homes. These style categories take on a greater variety of omitted characteristics than semi-detached, condo, and row homes. OPA's apartments category contains highly varied characteristics, many of which OPA omits, so this result agrees with Payton (2014), who finds structural heterogeneity on both a property and neighbourhood-level increases overassessment (p 14).

Lower median income is the neighbourhood demographic characteristic that increases overassessment risk the most. Further, apartments in higher-income tracts experience lower average overassessment than single family homes, but apartments in lower-income tracts experience higher average overassessment. Additionally, results for properties in mixed-use and apartment zoned districts conflict with those for properties that are mixed-use and apartments themselves. Table 3 shows the share of total residential properties that are apartments and mixed-use buildings to be below 1%. Similarly low is the share located in mixed-use and apartment-only zoned districts. However, Table 12 in Annex 5 shows overassessment's conditional variances are extremely high for all styles and types, thus ruling out higher variability as an explanation for these counter-intuitive findings for these specific categories with a smaller share.

Average overassessment also intensifies when property styles are considered alongside income level, putting those who sort into semi-detached, condo, and row homes in lower-income tracts at an additional risk of overassessment. This additional overassessment risk is higher for row homes in lower-income tracts but not for higher minority population, as expected given Adelman (2004) and Logan's (2013) evidence of neighbourhood segregation by race and ethnicity. This is possibly explained by a recent trend noted by Kramer & Kramer (2018) that "income and wealth based segregation is growing even as racial segregation is slowly subsiding" (p. 17), though spatial sorting patterns across property styles, neighbourhood, and demographics must first be solidified.

Overassessment cannot be attributed to OPA's omissions of certain style-specific characteristics alone. Avenancio-Leon & Howard (2022) conclude that demographic sorting into neighbourhoods with characteristics omitted from valuation models is the reason for high overassessments and thus do not distinguish between model-based error for property characteristics and assessor bias for demographic factors (p. 8). However, I attempt to isolate model-based error from assessor bias rather than attribute demographic overassessment to sorting. Here, average overassessment increases with tract Hispanic and Black population. Further, certain styles have different overassessment risk when their tract Black, Hispanic, and Asian shares increase. These differentials may be linked to assessors' individual biases that percolate through the system. However, considering the high risk of endogeneity in my models there may be additional highly localised characteristics that better link these differentials to OPA's omissions. These may include distance from the central business district Berry & Bednarz (1975) or traffic congestion (Chun & Linneman, 1985, p. 9).

What is the likelihood that overassessed properties become delinquent and reach foreclosure?

From 2015-2022, 9.8% of overassessed delinquent properties reached tax foreclosure. Overassessment is only significant when high relative to income level, and this shock only increases the odds of delinquency by .004%. This is likely underestimated given that zones with the greatest overassessments (G and H) are missing from OPA's data. Lower-income tracts see both higher average overassessment and higher delinquency odds. This supports the literature on delinquency as a metric of financial distress including Carroll & Goodman (2017) and Wong (2023). Application of Alm et. al's (2016) "delinquency discount" can establish how this overassessment and delinquency risk may lead to depressed sales values and delinquency spillovers for lower-income neighbourhoods. While there is some delinquency risk from higher overassessment alongside lower income, overassessment does not act as an additional financial shock over general assessment increases as found in Fu (2022).

Delinquency risk varies largely by zone and year. Case profiles Zones D and F are necessary to explain why zone location significantly increases a property's delinquency risk more than overassessment. The loss of significance in delinquency odds given overassessment upon consideration of year suggests underlying temporal factors put forth by Bahl et. al (2010) such as economic or real estate market conditions increase delinquency odds moreso than overassessment.

Overassessment is seen to increase tax foreclosure odds between 18.2% and 118.5%, but only six years after the initial overassessment, and this relationship does not hold once the year of foreclosure is considered. Foreclosure estimates for race, ethnicity, and income are also not significant when considering year, with 81% of foreclosures from 2015-2022 occuring in 2021. Further study into the temporary enforcement easing for owner-occupied properties during the 2020 Covid-19 pandemic is needed to explain this spike, and why it exceeds pre-Covid foreclosure levels. Delinquency and foreclosure odds also exhibit different behavior across the period, with delinquency steadily increasing and foreclosure fluctuating. Household-level determinants of foreclosure remain unclear.

4.3.2 Implications

Research and practical implications derived from empirical findings touch on the following three areas:

1. Social exigency for overassessment reduction
2. Fiscal exigency for assessment reform

3. Viable assessment model alternatives

4.3.2.1 Social exigency

The relationship with race and ethnicity should be examined with greater accuracy and precision in future studies, that is, more effectively imputed on the property level. The focus here is on the impacts of neighbourhood level race and ethnicity. However, for delinquency risk, solidifying overassessment as an additional shock may require household rather than tract-level income data. Household-level race and ethnicity may also have a different relationship to delinquency than race and ethnicity as a neighbourhood feature as tested here, but such entails more sophisticated imputation techniques than currently available.

Further research into the neighbourhood-level may pursue other measurements for minority profiles. For example, this study compares changes in average overassessment when each minority group's share incrementally increases within a tract, but another method is measuring the majority-minority threshold. Additionally, the Census's Prevalence Ranking shows different rankings of racial and ethnic groups. For instance, effects when a tract's largest group is Black, second Asian, and third White versus when a tract's largest group is Black, second White, and third Asian. Prevalence rankings offer additional nuance into tract racial and ethnic profiles, which may further understanding on sorting behaviour and assessor bias.

This study is narrowed to tax foreclosure, but there are a number of other less severe outcomes that beg further research. Financial distress can occur as households take action to avoid delinquency, and delinquency can result in displacement without tax foreclosure. Households may have to choose between making property tax payments and mortgage payments (Hwang & Ding, 2020). If mortgages go unpaid, credit scores suffer and if they go into default then houeseholds reach mortgage foreclosure (Bradley, 2013, p. 30). If tax bills are paid late or in instalments, households accrue fines or monthly interest on tax debt (Bradley, 2013, p. 3). Bradley (2013) and Hwang & Ding (2020) argue that mortgage default and foreclosure may occur if households neglect mortgage payments for tax bill payments, and posit that credit scores are a promising measure of vulnerability for residential displacement. The relative risks of tax foreclosure and mortgage foreclosure require further study, given that the former is more lenient and takes years while the latter takes months. These relative risks are interesting in the Philadelphia case given its low mortgage rate. Additionally, understudied are the prolonged pressures of repeated overassessment that can result in displacement without delinquency and foreclosure. Thus far only pressures from general assessment increases are investigated, with "evidence that property tax pressure can trigger involuntary moves by homeowners" (Martin, 2016, p.1), and "tax motivated moves" from repeated increases (Fraenkel, 2021, p. 22). Distress and displacement can occur as households take action to avoid tax foreclosure. Empirical consensus on these avenues may aid in describing the behavioural responses to overassessment in Philadelphia and nationwide.

Overassessment is found here to have a positive, albeit small, association with rental properties of moderate and high density, being multifamily, mixed use, and apartments in lower-income tracts. A further breakdown of valuation model treatment of apartment sub-styles and their neighbourhood profiles is thus warranted. Broader research on overassessment's impacts on renters is similarly ambiguous, but should build on Fu (2022) and Fraenkel (2021) who connect assessment increases to tax capitalisation. Rental capitalisation is a common practice whereby landlords pass on property tax costs to renters. The impact of such on renters is more difficult to identify than delinquency, but doing so is important because rental properties do not qualify for tax exemptions in Philadelphia so there is no offsetting of overassessment. Tracing rental increases and evictions from capitalised overassessments should be conducted despite these challenges.

As an incision into assessment modelling, this study abstracts away from property tax policy. While targeted exemptions are found not to reduce tax foreclosures for low-income households in Detroit (Eisenberg et. al, 2020), such have not been examined in detail in Philadelphia. A natural progression is policy analysis into if and how measures such as credits, deductions, deferrals, and instalment plans can offset overassessment and prevent delinquency. In Philadelphia these are the Longtime Owner Occupants Program, the Homestead Exemption, and the Senior Tax Freeze.

4.3.2.2 Fiscal exigency

Findings confirming overassessment in Philadelphia of up to 135% pose a risk of litigation. Precedent cases for court-ordered system overhauls include Lerner v. Davenport (2011), Fradenburg v. City of Lakewood (2015), and Zelinsky v. Board of Review of the Village of Westmont (2018). Mandated system overhauls have included AI-based pathways and digitalisation (Maricopa County Assessor's Office, 2020), in one case resulting from "Residential properties in Hispanic and Black census tracts (being) twice as likely as those in White tracts to be overassessed by 20 percent or more" (Grotto & Dardick, 2017). The risk of tax refunds to overassessed properties also continually mount given class action lawsuit outcomes. Revenue losses from these refunds have, in a case in Jackson County, reached the magnitude of 10% of the municipal budget (Chan, 2024; Merchant, 2024). Reducing litigation risk is possible with proactive effort from OPA towards demographic overassessment reduction, here most evident in higher Black and Hispanic share tracts.

While the literature demonstrates how systematic overassessment results in disparate revenue distribution, delinquency and foreclosure better explain Philadelphia's falling property tax revenues overall. High delinquency and subsequent foreclosure are sources of revenue shortfalls (Alm et.al, 2016). This is partially attributed to spatial spillovers documented by Carroll & Goodman (2017), which render properties as non-revenue generating as described by Chirico et.al (2016). This phenomenon is evident in the aforementioned case studies in Indianapolis, Chicago, Detroit, and Milwaukee, spiralling into a fiscal crisis in the Detroit case (Martin, 2016; Alm et.al, 2016; Atuahene and Berry, 2019; Carroll & Goodman, 2017). Properties in Zones D and F are more likely to be delinquent, so the presence of within-zone spillover effects and revenue shortfalls is a point of further attention for Philadelphia. Additionally, Fu (2022) establishes that household delinquency snowballs across time, especially for Black households in Philadelphia (p. 23). Understanding the revealed steady annual rise in delinquencies necessitates identification of the specific underlying temporal economic conditions and additional household-level drivers of delinquency risk.

Year fixed effects exhibit persistent increases in delinquency probability but fluctuations in foreclosure probability. How annual interest rates and real estate market conditions impact delinquency and foreclosure differently may eludicate this behaviour. In addition, foreclosure spillovers both decrease revenue and pose substantial costs, often resulting in a net negative revenue effect as shown in Atuahene & Berry (2019) and Alm & Leguizaman (2018). Governments receive proceeds from tax foreclosure sales, but sell at a discount from market value or fail to sell (Carroll & Goodman, 2017 p. 10), making proceeds often insufficient to cover the costs of the auction process. Annual fluctuations in foreclosure may pose a risk of highly volatile administrative costs coupled with depressed and stable revenue to fund such administration. A deeper look into tax foreclosure prevention for fiscal solvency could address this potential revenue and cost stability mismatch.

4.3.2.3 Assessment Model Alternatives

Random property-level errors such as misclassifying individual properties, inputting incorrect data, or misapplying the valuation model are not seen. Semi-automated processes such as selection of comparables and model specification mentioned in Table 1 are thus more likely sources of overassessment. Philadelphia's new iasWorld system is interoperable with low-cost add-on software (IAAO, 2022, p. 4), which other cities have used to adopt AVMs. This software includes big data databases needed for AI-based ANNs, which remove the risk of human bias present in the zone-level comparables selection and MLR specifications.

ANNs have seen adoption in property valuation by private appraisers prioritising accuracy (Kilpatrick, 2011) alongside academic studies that successfully test ANNs on citywide data by simulating municipal mass appraisals. ANNs vetted by both private appraisal and academia are considered in Table 7. Accuracy performance is included given this study's evidence of high levels of overassessment and a need for improved accuracy overall.

The transition to an additional add-on software is however a leap given the lack of cost recovery, vendor lock-in from iasWorld, and high staff training requirements. Without this add-on, iasWorld's GIS database integration does allow for geographically-weighted regression (GWR). This model may temper the high rate of overassessment for row, semi-detached, and condo homes by better accounting for spatial and neighbourhood value effects. Such an approach has been recommended to OPA by independent auditors but have not yet been pursued (Gloudemans, 2019). While GWR is more transparent (McCluskey et. al 2012, p. 16) and readily compatible with iasWorld than other alternatives, it does not offer as large of an accuracy improvement.

Table 7:Summary of Automated Valuation Models

AVM	Description	Accuracy
Artificial Neural Networks (ANN)	ANNs extract patterns between input and output data by mimicking heuristics of the human brain.	ANNs perform best in predictive accuracy (McCluskey & Adair, 1997, p. 71; McCluskey et. al, 2013, p. 318). They are preferred for handling highly differentiated properties (Pagoutzi et.al, 2003, p. 13).
Kohonen Self-Organising Maps	A type of unsupervised ANN, these models extract patterns by segment properties into clusters based on similarity.	The highest performing ANN with municipal adoption (Lewis et. al 1997; McCluskey et, al, 2018). Its clustering technique is well suited for drawing zones of comparable properties.
Geographically Weighted Regression	Property characteristics are locally weighted to capture variation by spatial sub-markets.	Performs best in reducing neighbourhood-level inaccuracy as evident in municipal adoption (Bidanset et.al, 2019).

5. Conclusion

Throughout the United States, residential overtaxation is frequently traced to overassessment of property value through cities' multiple linear regression valuation models. Philadelphia is chosen as a case here as assessment practice lies at an intersection of issues faced by the city including property tax revenue shortfalls (Dowdall & Warner, 2012), increasing tax reliance on residential properties (Hincken, 2022), and a high tax delinquency rate (Eichel & Ginsberg, 2019). The city's assessment model has been scrutsinised by local advocacy groups and assessment industry organisations as exacerbating uneven tax burden distribution by systematically overassessing residents (Philadelphia Forward, 2003). The Office of Property Assessment's Computer Assisted Mass Appraisal model adjusts sales values for individual properties' structural characteristics to estimate market value. These adjustments best describe features of single detached homes despite the city's large stock of row and semi-detached homes with heterogeneous characteristics.

Research throughout the U.S. has examined how models produce overassements across structural and locational characteristics, and how these can carry through to certain demographic groups. Recently, criticisms of standard assessment models have argued overassessment as a case of algorithmic discrimination. Another branch of the property tax literature is concerned with delinquency and tax foreclosure as they related to general assessment increases, but do not link these metrics of financial distress to model-based discrimination in the form of overassessment. This study begins by asking what factors are associated with residential property overassessment in Philadelphia, then how overassessment is related to delinquency and tax foreclosure.

Four main hypotheses are put forth to fulfill these objectives, being that overassessment has a positive association with racial and ethnic minority share, a negative association with income level, a positive associations with both the probability of delinquency and tax foreclosure. The empirical strategy proceeds by running a series of panel data regression models on the OPA's property-level data matched with U.S. Census Bureau tract-level demographic data. First, random effects regression serves to control for random assessment error and isolate structural, locational, and demographic relationships to overassessment. Secondly, fixed effects regression is used to control for effects within years and sub-jurisdictional zones in aiming to estimate precise probabilities for deliquency and tax foreclosure at different levels of overassessment.

Overassessment is found to relate to a property's structural similarity to single family homes and on its tracts' median income level. In descending order, row homes, condos, and semi-detached homes are consistently highly associated with overassessment relative to single detached homes. Properties' also see higher average overassessment with a higher tract Hispanic population. Average overassessment is magnified for properties with both higher tract Hispanic population and multifamily (moderate density) than single family (low density) zoning designation. A limitation is that OPA's non-random overassessment is not fully explained by the property, locational, or demographic characteristics considered.

This is the first analysis of systematic overassessment across all residential property styles in all zoning designations in Philadelphia. Non-random overassessment is evident, but identifying and correcting for systematic factors of overassessment in Philadelphia requires more advanced modelling both in academic testing and assessment practice. There is an opportunity to deepen this study's findings as OPA's new iasWorld system offers higher quality property data. For example, improvements are anticipated for characteristics and sales data for Zones G and H, which are missing in this study's analysis of data that is otherwise on the full population of non-vacant residential properties. While significant, zoning designation only accounts for minimal overassessment variation in this study, so other locational characteristics may better capture sub-market and neighbourhood value in Philadelphia. GIS integration in iasWorld allows OPA to provide property-level geospatial data, presenting a possibility for identifying these locational value characteristics. Explaining related changes in demographic overassessment through sorting across these identified characteristics would both help pinpoint OPA's bias and error sources and contribute to the broader discussion on model-based and deliberate distortion as it pertains to algorithmic discrimination in assessments. To note, an additional limitation is this study's consideration of demographics only as a neighbourhood feature, so future analysis of non-random variation on property-level demographics must overcome challenges in household-level imputation techniques.

Pressure for targeted overassessment reduction is likely to intensify, and OPA can either continue their trajectory in favour of single detached homes or uptake methods better suited to the city's socioeconomic and structural diversity (OPA, 2024). While OPA cannot use race, ethnicity, and income to value properties, they can target overassessment reductions for neighbourhood features. OPA should leverage geospatial data collection capabilities available in new GIS database to facilitate identification of such characteristics as well as perform academic and municipal testing of GWR and other vetted spatial methods. Such can provide the basis for OPA's expansion in adjustment variables and adoption of alternative models. Though there is no silver bullet valuation solution, adopting ANNs in the long term is step towards a 'smarter' property tax system by reducing general overassessment, of which is evident in this study. Building trust in AVMs amongst a landscape already sceptical of MLR will require considerable long-term prioritisation from OPA, but the transition to iasWorld presents a window of opportunity for AVM-compatible software.

This study is also the first to test the relationship between overassessment and delinquency in Philadelphia, though tract-level demographic variables are found have higher delinquency probabilities. A property's delinquency probability is found to increase primarily with decreases in neighbourhood median income, and secondarily with increases in Black and Hispanic population. These results for neighbourhood-level demographics present an opportunity to deepen the discussion on spatial spillovers, for example in enriching Alm et. al's (2016) findings on the "delinquency discount" for sales values in neighbourhoods of high delinquencies and foreclosures. Again, refinement of statistical imputation techniques is required to narrow findings on household demographics and delinquency.

A persistent rise in delinquencies is evident, so policies for delinquency prevention should continue to intervene post-assessment to curb this trend. This study's findings on heightened delinquency risk for low-income neighbourhoods imply income-based abatement measures such as exemptions and credits may more effectively reduce delinquency than assessment model reform. However, delinquency risk has been linked to additional household-level financial factors such as mortgage escrow status (Bahl et.al, 2010; Bradley, 2013) and liquidity constraints (Chirico et.al, 2019; Hayashi 2020) which deserve research and research and policy consideration alongside income. With 49% of Philadelphia residents believing the property tax is unfair (Hincken, 2022, p.7), unpopularity is another another possible household driver. To note, not captured here are the behavioural responses to overassessment that are taken to avoid delinquency but may similarly manifest in household financial distress.

Lastly, this study sets a precedent in analysing the relationship between overassessment and tax foreclosure in Philadelphia, yielding no consistent significant relationship between the two. The year of sale carries the highest probability of tax foreclosure with large annual fluctuations, though these are included only as a control variable here. Unpacking these yearly fixed effects may involve exploring macro-level real estate market and economic conditions suggested by Bahl et. al (2010) to either increase a property's assessment relative to household income or decrease income relative to assessments. In Philadelphia, an analysis of the temporary Covid-19 easing of tax foreclosure sales is warranted to explain the dramatic foreclosure spike in 2021. In pursuing fiscal health, Philadelphia should prioritise delinquency and foreclosure prevention given the uptick in foreclosures and concomitant net negative revenue impact. However, like delinquency, policy interventions for tax foreclosure prevention at the household-level remain unclear. Important to capture in ongoing research are the behavioural responses to overassessment that are taken to avoid tax foreclosure but may similarly manifest in household displacement.

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Annex 2: Heteroskedasticity and Serial Correlation Tests

For Model 5 in Table 3, the risk of violating the assumption that all the random effects residuals are uncorrelated with the covariates is evident in the Breusch-Pagan test results. For all specifications this test rejects the null hypothesis that there is no heteroskedasticity in the residuals. The Pagan-Breusch-Godfrey also reject the null of no higher-order residual serial correlation.

Table 8: Breusch-Pagan Heteroskedasticity and Pagan-Breusch-Godfrey Serial Correlation Tests

Random Effects Residual Heteroskedasticity and Serial Correlation Tests

	Model1	**Model2**	**Model3**	**Model4**
Breusch-Pagan Test: Statistic	24,382	28,996	29,516	25,164
Breusch-Pagan Test: p-value	0	0	0	0
Pagan-Breusch Test: Statistic	999,138	999,235	998,484	999,004
Pagan-Breusch Test: p-value	0	0	0	0

MLR Residual Heteroskedasticity and Serial Correlation Tests

	Model1	**Model2**	**Model3**	**Model4**
Breusch-Pagan Test: Statistic	178,055	188,003	193,286	194,711
Breusch-Pagan Test: p-value	0	0	0	0
Durbin-Watson Test: Statistic	0.3085914	0.3090972	0.3095045	0.3091486

Annex 3: Zip-Code Fixed Effects

Table 9: Logit Regression Estimates on Delinquency with Zip-Code Intercepts

	Dependent variable:			
	Delinquent			
	(1)	(2)	(3)	(4)
Overassessment (*ln*) Lag 1	−0.007	0.108	0.082	0.085
	(0.0052)	(0.0915)	(0.0979)	(0.0968)
Demographics				
Neg Median Income (*ln*)	0.292***	0.358***	0.478***	0.665***
	(0.0746)	(0.0818)	(0.0885)	(0.1617)
Black Percentage	0.014***	0.014***	0.013***	−0.004
	(0.0014)	(0.0014)	(0.0014)	(0.0219)
Hispanic Percentage	0.010	0.010***	0.008***	−0.011
	(0.0014)	(0.0014)	(0.0015)	(0.0268)
Asian Percentage	−0.007	−0.007·	−0.008*	−0.163***
	(0.0041)	(0.0041)	(0.0040)	(0.0926)
Year Fixed Effects: 2015 Base				
2016			0.037*	0.039
			(0.0260)	(0.0261)
2017			0.037	0.037
			(0.0292)	(0.0298)
2018			0.071*	0.072*
			(0.0341)	(0.0346)
2019			0.093*	0.095*
			(0.0372)	(0.0378)
2020			0.149***	0.149***
			(0.0441)	(0.0444)
2021			0.178***	0.178***
			(0.0453)	(0.0457)
2022			0.228***	0.228***
			(0.0517)	(0.0526)
Interaction Terms				
Neg Median Income (*ln*): Overassessment (*ln*) Lag1		0.011	0.008	0.009
		(0.0085)	(0.0090)	(0.0089)
Neg Median Income (*ln*):Black Percentage				−0.001
				(0.0020)
Neg Median Income (*ln*):Hispanic Percentage				−0.001
				(0.0026)
Neg Median Income (*ln*):Asian Percentage				−0.014·
				(0.0086)
Observations	3,593,310	3,593,310	3,593,310	3,593,310
Log Likelihood	−905,815.400	−905,269.500	−917,891.200	−905,202.100
Bayesian Inf. Crit.	1,812,400.500	1,811,429.600	1,836,069.200	1,833,659.300
Adj. Pseudo R2	0.0871	0.0873	0.0878	0.0879
Note:				*p<0.1; **p<0.05; ***p<0.01

Annex 4: Census Tract Fixed Effects

Table 10: Logit Regression Estimates on Delinquency with Census Tract Intercepts

	Dependent variable:			
	Delinquent			
	(1)	(2)	(3)	(4)
Overassessment (*ln*) Lag 1	−0.01***	0.140*	0.133*	0.118*
	(0.0028)	(0.0574)	(0.0593)	(0.0120)
Demographics				
Neg Median Income (*ln*)	−0.001	0.085*	0.112***	0.311***
	(0.0121)	(0.0351)	(0.0329)	(0.0223)
Black Percentage	0.001*	0.001**	0.001***	−0.019*
	(0.0005)	(0.0005)	(0.0004)	(0.0075)
Hispanic Percentage	0.001***	0.001**	0.001*	−0.010*
	(0.0005)	(0.0005)	(0.0005)	(0.0054)
Asian Percentage	0.000	0.000	0.000	0.003
	(0.0009)	(0.0009)	(0.0008)	(0.0167)
Year Fixed Effects: 2015 Base				
2016			0.029*	0.032**
			(0.0122)	(0.0121)
2017			0.027*	0.032*
			(0.0130)	(0.0129)
2018			0.030*	0.038**
			(0.0132)	(0.0178)
2019			0.026*	0.038**
			(0.0129)	(0.0143)
2020			0.032*	0.056**
			(0.0136)	(0.0083)
2021			0.039**	0.066**
			(0.0140)	(0.0208)
2022			0.043*	0.077**
			(0.0142)	(0.0250)
Interaction Terms				
Neg Median Income (*ln*): Overassessment (*ln*) Lag1		0.014**	0.013*	0.012*
		(0.0011)	(0.0054)	(0.0056)
Neg Median Income (*ln*):Black Percentage				−0.002*
				(0.0003)
Neg Median Income (*ln*):Hispanic Percentage				−0.001*
				(0.0005)
Neg Median Income (*ln*):Asian Percentage				0.000*
				(0.0016)
Observations	3,593,044	3,593,044	3,593,044	3,593,313
Log Likelihood	−897,663.400	−-897,588.4	−897,576.800	−-897,589.700
Bayesian Inf. Crit.	1,800,126.800	1,799,991.900	1,800,074.300	1,800,507.600
Adj. Pseudo R2	0.0952	0.0952	0.0953	0.0952
Note:				*p<0.1; **p<0.05; ***p<0.01

Annex 5: Variability Measures

Table 11 displays the conditional variances and related percentage changes for when each property style and type categorical dummy variable takes a value of 1. Conditional variances in property styles are taken when the property type is set to the reference category of single family, and conditional variances for property types set the style reference category to single detached.

Table 11: Property Style and Type Conditional Variances

	Conditional Variance	Percentage Change
Property Style		
Semi Detached	15.48	5018.04
Row	15.48	5018.92
Apartment	15.51	5037.41
Condo	15.48	5018.74
Mixed	15.50	5029.69
Property Type		
Multi family	15.54	5054.64
Mixed Use	15.51	5037.44
Apartments	15.48	5018.70

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