Impact of Housing Demand Shocks on Home Appraisal Precision: Insights From The Shift To Work From Home During The COVID-19 Pandemic *

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Abstract

This paper analyzes the effects of the recent housing demand shock triggered by the shift to remote work during the COVID-19 pandemic on the precision of home appraisals. Between 2013 and 2019, approximately 10% of home appraisals in the United States and its 12 largest cities fell below the negotiated contract price. However, this figure saw a dramatic surge in 2021, with an astonishing 96% increase across the United States and a 128% rise in the 12 largest cities, coinciding with a rapid escalation in home prices. Insights from a canonical urban model of housing in cities and a simple property value estimation model indicate that appraisers initially underestimated the changing market conditions and the spatial concentration of housing demand, causing their evaluations to lag significantly behind the housing demand increase. Over time, however, appraisers gained a better understanding of these dynamics. I find a notable rise in the likelihood of appraisals falling below contract prices during the first two years of the COVID-19 pandemic, with these increases predominantly occurring in suburban areas which also experienced the highest demand increase due to the work-from-home shift. Additionally, the gap between contract prices and appraised values widened significantly during this period, particularly in suburban markets.

Keywords: Home Appraisals, Housing Demand, Work From Home, Bid-Rent
JEL Codes: D01, R21, R30

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1 Introduction

The rise of work-from-home (WFH) practices, accelerated by the COVID-19 pandemic, has significantly transformed the dynamics of urban life and labor markets. Prior to the pandemic, many workers were tethered to high-cost urban centers due to the proximity of jobs, but the widespread adoption of WFH has reduced the necessity for employees to live near their workplaces (Dingel and Neiman, 2020). As a result, commercial real estate has experienced a notable decline in demand, particularly in central business districts and dense urban areas where office spaces once thrived. Office occupancy rates have dropped along with the appeal of densely packed neighborhoods where jobs and consumption amenities are spatially concentrated (Liu and Su, 2021; Gupta et al., 2022). Central Business Districts of the largest 12 US cities have seen net population and business outflows cumulating to around 9% and 16% of their pre-pandemic levels (Ramani and Bloom, 2021).[1] This transformation could have lasting impacts on urban planning, infrastructure investments, and housing markets as cities adapt to a more flexible, dispersed workforce.

The WFH shift has allowed many workers to relocate to more affordable or desirable areas, altering traditional patterns of housing demand and reshaping urban geography. Real estate demand, as measured by rents and prices, has increasingly shifted away from major city centers toward lower-density areas on the outskirts of cities. This shift also reflects a growing preference for larger homes and more space as the need for daily access to the city center for work has become less critical (Duranton and Handbury, 2023). Extensive research has documented that the growth in demand for less densely populated areas has contributed to a flattening of the housing-price gradient (Liu and Su, 2021; Mondragon and Wieland, 2022; Gupta et al., 2022; Duranton and Handbury, 2023; Ramani and Bloom, 2021; Hansen et al., 2024; Gamber et al., 2023; Monte et al., 2023; Brueckner et al., 2023). In other words, the price differential between city center properties and those in peripheral areas has narrowed, reflecting the changing priorities and flexibility of a workforce less tied to a daily commute. Ramani and Bloom (2021) label this the "Donut Effect", reflecting the hollowing out of city centers and growth of suburban outer rings. This phenomenon is reshaping urban housing markets and contributing to changes in both urban land use and the internal structure of cities.

A key area that remains unexplored in the literature entails understanding how home appraisers reacted to this sudden, systematic surge in housing demand and what impact did this have on real estate asset valuations. While home prices began to soar at the onset of the pandemic, one insight documented in the literature is the fact that we saw a larger impact on the rent gradient relative to the home price gradient (Liu and Su, 2021; Gupta et al., 2022; Ramani and Bloom, 2021). A potential mechanism detailed in the literature that could explain this pattern concludes that home prices are forward looking and the market anticipates that future demand for central locations could bounce back to some degree in the long run.

In this paper I explore a different channel, the direct role appraisers have on transaction prices through home appraisals, that in practice, should be based on market fundamentals. Between December 2019 and December 2021, U.S. home prices surged by an unprecedented 25%, marking the fastest rate of growth on record. This housing boom was largely driven by workers relocating to less dense, suburban, and rural areas as the rise of WFH made proximity to the office less

[1] The largest 12 Metropolitan Areas in the United States, namely: Atlanta, Boston, Chicago, Dallas, Houston, Los Angeles, Miami, New York City, Phoenix, Philadelphia, SanFrancisco, Washington DC.

important. As a result, housing markets in the suburbs experienced a significant increase in activity, with median days on the market—a key indicator of housing liquidity—dropping sharply in these areas (Gupta et al., 2022). At the same time, inventory levels in city centers grew, further signaling a spatial shift in demand away from high-density areas (Liu and Su, 2021). The combination of record-low interest rates, the desire for more living space, and the newfound flexibility afforded by WFH policies contributed to a boom in suburban housing markets, while urban centers, once the epicenters of housing demand, saw a cooling in prices and slower turnover.

During the housing boom and bust of the early 2000s, appraisers played a controversial role in inflating property values, contributing to the eventual market collapse. As demand for homes surged and lending standards loosened, many appraisers faced pressure from lenders, mortgage brokers, and real estate agents to provide higher appraisals to secure larger loans. Some appraisers succumbed to this pressure, inflating home values beyond their true worth, which allowed buyers to borrow more than the property was worth (Conklin et al., 2020; Kruger and Maturana, 2021; Shui and Murthy, 2019; Calem et al., 2021; Mayer and Nothaft, 2022). This overvaluation created a bubble, with home prices soaring artificially. When the bubble burst, many homeowners found themselves owing more on their mortgages than their homes were worth, leading to widespread foreclosures and a collapse in the housing market. The lack of stringent regulation and oversight allowed this practice to proliferate, exacerbating the financial crisis that followed.

To address these concerns, new regulations were introduced to reduce conflicts of interest and improve the accuracy of property valuations. The Home Valuation Code of Conduct (HVCC) was implemented on May 1, 2009, following a joint agreement between Fannie Mae, Freddie Mac, the Federal Housing Finance Agency, and the New York State Attorney General. Later, key provisions of the HVCC were incorporated into the Dodd-Frank Act of 2010. Under the HVCC, lenders are prohibited from pressuring appraisers to reach a predetermined value for a property, ensuring more independent and unbiased assessments. Subsequent research finds short-run evidence that HVCC led to reductions in inflated valuations at the time of its initiation. (Shi and Zhang, 2015; Shui and Murthy, 2018; Agarwal et al., 2016; Ding and Nakamura, 2016). However, while the 2009 HVCC and the appraisal-focused reforms in the 2010 Dodd-Frank Act addressed known conflicts of interest between lenders and property appraisers, they did little to change the methods that appraisers use, which result in biased valuations. To design more effective reforms and assess the economy's vulnerability to future crises, it is crucial to gain a deeper understanding of the motivations, mechanisms, and harm caused by appraisal bias (Eriksen et al., 2024).

Was the surge in home prices during the shift to remote work driven by real changes in market fundamentals, or was it simply another bubble fueled by 'irrational exuberance', reminiscent of the early 2000s? In home purchase transactions, the mortgage appraisal also holds significance for the buyer, serving as a safeguard against overpaying when housing bubbles emerge by providing the appraiser's opinion on the property's value. However, the WFH induced housing boom was quite different from the boom of the early 2000s. Mondragon and Wieland (2022) show that the shift to remote work accounts for at least one half of aggregate house price growth over this period. their results suggests that house price growth over the pandemic reflected a change in fundamentals rather than a speculative bubble, and that fiscal and monetary stimulus issued during this time were less important factors. Gamber et al. (2023) also find supporting evidence of this being the case.

In this paper I analyses the impact of the Covid-19 induced WFH shift on the accuracy of home appraisals in the 12 largest Metropolitan Areas in the United States.[2] To interpret the home appraisal data, I consider the WFH shock in a canonical urban model of housing in cities in the tradition of (Alonso, 1964; Muth, 1969; Mills, 1967) as presented in (Duranton and Puga, 2014, 2015; Duranton and Handbury, 2023) to explain the evolution of the housing market over first two years of the Covid-19 Pandemic. A simple urban model where residential choices depend only on housing and commute costs matches the short-run response to the WFH shock that we observe: when most of the workforce is working from home, prices increase in the suburbs and decline near city centers. I also present a simple stylized model of the property value estimation process from the perspective of an representative appraiser as presented in Geltner and Ling (2006) to conceptualize an appraisers best response to a sudden housing demand shock when determining the value of a subject property. Insights from this model show how selecting the proper amount of nearby recent transactions with similar characteristics as the subject property has influence on whether a property will appraise below the negotiated contract price and more so when there is a housing demand shock.

To empirically examine the impact of the shift to remote work on home appraisal precision,[3] I analyze a dataset of appraisal records provided by the Federal Housing Finance Agency. This dataset includes key data fields from appraisal reports, such as the negotiated contract price, appraised value, and property characteristics. The dataset consists of a nationally representative five percent random sample of arm's-length single-family mortgage appraisals acquired by Fannie Mae and Freddie Mac between 2013 and 2021.

The primary objective of an appraisal is to furnish an impartial and efficient valuation of a property's market value for both the buyer and the originator. Precise property valuation is crucial information for the entity holding credit risk in a mortgage. To determine the Loan-to-Value (LTV) ratio linked to the mortgage, lenders consider the lesser of the appraised value and the sale price in purchase transactions, and solely the appraised value in refinances. Traditionally, appraisers determine property value using three approaches: sales comparison, cost, and income. The sales comparison approach is predominantly applied to residential properties. In this method, the appraiser usually locates recent sales of nearby properties with similar characteristics, referred to as "comparable properties" or "comps." The appraiser then makes adjustments to the sale prices of comparable properties based on noticeable physical differences in property characteristics. Following the consideration of both structural and non-structural property characteristics, the appraiser assigns a final weight to each adjusted comp, ultimately arriving at a final weighted average appraised value for the subject property.

Before the onset of the Covid-19 pandemic, most homes appraised above contract price roughly 60-65% of the time while 25-30% appraised at contract price (Rothwell and Perry, 2022). As indicated in Figure 1, the yearly incidence of appraisals falling below the contracted price was typically below 10%, from 2013 to 2019 throughout the United States and the 12 largest metropolitan areas. However, there was a significant surge in appraisals below contract price, reaching 15 percent

[2] Ramani and Bloom (2021) document that the donut effect is primarily a large city phenomenon. Outside of large, dense metro areas they do not observe much divergence in price growth, or population or business outflow between the CBD and lower density areas. The authors find that the donut effect is more widespread when measured through rental growth but is still primarily a large-city phenomenon.

[3] Accuracy measures how close a measurement is to the true value, while precision measures how consistently repeated measurements align with each other. These two concepts are independent; you can be highly precise without being accurate, and vice versa.

for the U.S. and almost 19 percent for the 12 largest metros in the year 2021, coinciding with a rapid escalation in home prices. This sudden change amounts to a staggering 96% increase for the United States and a 128% increase for the largest metros! The growth in both home prices and appraisals below contract price began reverting closer to more standard levels by early 2022 and continued through 2023.

One possible explanation for this variation is that appraisers often rely on recent comparable property sales, which can quickly become outdated during periods of rapid price fluctuations. An appraised value below the contract price can negatively impact the real estate transaction in several ways such as; the buyer may be forced to make a larger down payment, the seller may have to reduce the agreed-upon sale price, or the sale could be canceled or significantly delayed (Fout and Yao, 2016). Such undervaluations can also impact refinance borrowers by influencing less favorable loan terms. In theory, appraisers have the flexibility to account for price fluctuations since the time comparable properties were sold by making adjustments, commonly referred to as "time adjustments" or "market condition adjustments" (Susin, 2024). Both Fannie Mae, Freddie Mac, and the Federal Housing Administration appraisal guidelines mandate these adjustments in situations where market conditions have undergone changes.

In this paper I find supportive evidence that the 128% increase in home appraisals coming in below contract price in 2021 for the 12 largest metros was in part due to appraisers not fully capturing how housing demand increased and shifted geographically due to WFH. I find a significant increase in the probability of an appraisal coming in below contract price during the first two years of the Covid 19 pandemic and that these increases were mainly focused in suburban areas where housing demand increased the most. As a measure of the extensive margin, I find evidence that the contract price and appraised value difference also significantly increased during this time, mainly in suburban areas.

Insights from the appraisal data through the lens of a urban model of housing in cities suggest that appraisers' judgement of the change in market conditions and spatial concentration of housing demand were rather conservative and lagged the WFH shock but appraisers gradually gained better insights over time. I use this geographic variation in housing demand to address the fact that the contract price may not be the ideal benchmark for the appraised value of a home. I make the assumption that differences between the contract price and appraised value do not vary in a systematic way with respect to proximity to downtown areas pre-Covid 19. From 2017 to 2019 the difference between the percent of appraisals below contract price in the suburbs vs the CBD was roughy 3% over this time. This difference roughly doubled to 6% in 2020 and grew to a staggering 11% in 2021, more than tripling the 2017-2019 average. This percent change is mainly due to increases in the suburbs, percentages in the CBD remained roughly constant over this time relative to suburban areas.

Consistent with the predictions of a stylized property value estimation model regarding price dispersion, I also find that appraised values tended to deviate further away from the contract price as the density of appraisals deceased within a given census tract. As more homes sold within a census tract this difference converges rapidly towards 0. This patterns suggests that appraisal estimates were highly effected by the density of transactions within a given census tract during the peak of the WFH housing demand increase. Aligned with the model's predictions concerning temporal lag bias, I also find that when appraising homes for which all the comps used were within the same census tract as the subject property, homes appraised using 7 or more comps tended to come in below contract price more often relative to homes appraised using 4 comps. This highlights the fact that when home prices are rapidly increasing, comps further back in time tend to not reflect current market conditions and can cause a "lag bias" in appraisal estimates if proper adjustments are not made.

The primary task of a home appraiser is to produce the best possible estimate of the market value of a subject property. In private real estate markets, market values are not directly observable to the appraiser, however, this does not mean they don't exist. The greater the uniqueness of the asset and the frequency at which the housing market is changing, the harder it becomes to accurately estimate market values. The future path of demand may depend critically on the path of remote work. If remote work reverses, then there may be a general reversal in housing demand and potentially house prices Mondragon and Wieland (2022). Gaining better insights into the trajectory of housing demand as the WFH trend progresses should be of high priority amongst home appraisers.

The remainder of this paper is organized as follows. Section 2 outlines the appraisal process and reviews the related home appraisal literature. Section 3 presents the various data sources used for analysis. Section 4 outlines the WFH shock in a canonical urban model of housing in cities to interpret the home appraisal data. Section 5 presents a conceptual framework of property value estimation and outlines a simple stylized model to interpret the home appraisal data. In Section 6 the empirical results are discussed. Section 7 concludes the paper.

2 The Appraisal Process and Related Literature

2.1 The Appraisal Process

2.1.1 Sales Comparison Approach

Conducting property appraisals is a standard practice in mortgage lending. The primary objective of an appraisal is to furnish an impartial and efficient valuation of a property's market value for both the buyer and the loan originator. By doing so, the originator fulfills its obligations to the ultimate holder of credit risk, which may include entities such as Government Sponsored Enterprises (e.g., Fannie Mae and Freddie Mac), Federal Housing Administration (FHA), the U.S. Department of Veterans Affairs, or the U.S. Department of Agriculture in many cases. The appraiser, appointed by the lender, is typically paid through a flat fee paid out-of-pocket by the homeowner. The appraisal is carried out in accordance with the Uniform Standards of Professional Appraisal Practice (USPAP) and adheres to the specific requirements set forth by the lender.

Precise property valuation is crucial information for the entity holding credit risk in a mortgage. To determine the LTV ratio linked to the mortgage, lenders consider the lesser of the appraised value and the sale price in purchase transactions, and solely the appraised value in refinances. In home purchase transactions, the mortgage appraisal holds significance for the buyer, serving as a safeguard against overpaying by providing the appraiser's opinion on the property's value.

Traditionally, appraisers determine property value using one of three approaches: sales comparison, cost, and income. The sales comparison approach is predominantly applied to residential properties. In this method, the appraiser locates recent transactions of nearby properties with similar characteristics, referred to as "comparable properties" or "comps." The sale prices of these comps are considered the most reliable indicators of the subject property's market value. The precision of an appraisal is heavily dependent on the careful selection of appropriate comps that closely match the characteristics of the subject property.

The appraiser then makes adjustments to the transaction prices of comparable properties based on noticeable physical differences in property characteristics (such as bedrooms and bathrooms). For example, in instances where the comparable property is larger or has more bedrooms than the subject property, the sale price of the comp is adjusted downward to account for this dissimilarity. These adjustments collectively ensure a fair "apples to apples" comparison between the subject property and the comps. Further adjustments are made concerning observable attributes that are typically not discerned through valuation methods like Automated Valuation Methods (AVMs). In making these decisions, the appraiser relies on their expertise and familiarity with the neighborhood and/or region, a competence mandated by the USPAP guide for appraisers to exhibit. Following the consideration of both structural and non-structural property characteristics, the appraiser assigns a final weight to each adjusted comp, ultimately arriving at a final weighted average appraised value for the subject property.

As previously noted, an appraiser's valuation of a property heavily relies on their selection of comparable properties and the adjustments and weighting they apply to those choices. The inherent subjectivity in an appraiser's work allows for a reasonable justification of a range of values. For lending purposes, an appraiser exercises expert discretion to determine a single point value. In a purchase transaction where there's a contract price for comparison, the appraisal point value estimates can reasonably fall either above or below the contract price.

2.1.2 Market Condition Adjustments

One potential mechanism for the sharpe increase in appraisals coming in below contract price can be attributed to appraisers relying on recent comparable property transactions, which can quickly become obsolete during periods of swift price changes. Appraisers have the flexibility to account for price fluctuations since the time comparable properties were sold by making adjustments, commonly referred to as time adjustments or market condition adjustments.

Appraisers often use regression techniques to make time adjustments in property valuations. Appraisers typically collect data from the Multiple Listing Service (MLS), focusing on property sales within a specific geographic area and time frame, usually within the past 6 to 18 months, based on their discretion. The core data required for a time adjustment include transaction prices and transaction dates. The appraiser then uses a computer software program such as Excel to create a scatter plot, with sale price on the y-axis and sale date on the x-axis. A trend line is then added to the data, allowing the appraiser to visualize and quantify market trends over time.

The bivariate regression analysis produces a time coefficient that reflects the rate of price change over a given period (e.g., percentage increase or decrease per month). This coefficient allows the appraiser to quantify how much property values have appreciated or depreciated between the sale of a comparable property and the appraisal date. For instance, if the regression indicates a 1% monthly increase in property values, the appraiser would adjust the comparable property's sale price upward by 1% for each month between its sale date and the current date. It's important to note that if housing demand has increased, say over the past four months leading up to the appraisal, including transactions further back in time in the sample will result in a smaller regression coefficient. This, in turn, would lead to a smaller and less accurate time adjustment. In practice, when adjusting for market conditions, the appraiser may also factor in other elements such as property size, number of bedrooms, and neighborhood features, including nearby amenities. This process can also be done using computer software programs such as 'Gnumeric' or 'SPARK' that can provide a more user friendly approach to the task.

The geographic area selected for gathering comparable transactions plays a critical role in determining the final appraised value. In theory, an appraiser could use all property sales within the entire city of the subject property to make market adjustments. However, in practice, it's more effective to focus on a smaller, more specific area—such as the zip code, census tract, or even the neighborhood—provided there are enough transactions within the appropriate time frame. Another approach is to define a "competitive market segment", where the appraiser selects homes that directly compete with the subject property in the market. If two recent transactions are located in the same neighborhood, they may not belong to the same competitive market as the property being appraised.[4] For example, two homes that recently sold for \$750,000 and \$90,000 in the same neighborhood as the property being appraised will not be in the same competitive market for a subject property priced at \$200,000.

Susin (2024) finds that appraisers often neglect to incorporate time adjustments, even in cases where they could significantly influence the appraised value. Additionally, the analysis also indicates that the adjustments made by appraisers are generally considerably smaller than what house price indexes would imply. In theory, even if no time adjustments are made, appraisers have other tools at their disposal that could prevent an appraisal from coming in below contract price such as assigning greater weight to more recent comps. More detail on these techniques are discussed later.

Both Fannie Mae, Freddie Mac, and FHA appraisal guidelines mandate these adjustments in situations where market conditions have undergone changes. Ultimately, how these adjustments are made are at the discretion of the appraisers. According to Chapter 5605 of Freddie Mac Appraisal Requirements: *"The appraisal report must include time adjustments to reflect any change in market conditions over the period analyzed. This is essential to determine an accurate market value for the subject property. Time adjustments reflect market condition changes from the time a comparable went under contract to the effective date of the subject property appraisal. Adjustments may be either positive or negative and should be supported by comparables that may include listings, contract sales or closed sales. The appraiser must provide an explanation for the use of time adjustments."*

2.2 Literature Review

2.2.1 2000s Housing Boom and Appraisal Inflation

During the housing boom and bust of the early 2000s, appraisers played a controversial role in inflating property values, contributing to the eventual market collapse. As demand for homes surged and lending standards loosened, many appraisers faced pressure from lenders, mortgage brokers, and real estate agents to provide higher appraisals to secure larger loans. Some appraisers succumbed to this pressure, inflating home values beyond their true worth, which allowed buyers to borrow more than the property was worth. This overvaluation created a bubble, with home

[4] As suggested by George Dell, a highly respected professional appraiser, in his Valuemetrics Home Appraisal course

prices soaring artificially. When the bubble burst, many homeowners found themselves owing more on their mortgages than their homes were worth, leading to widespread foreclosures and a collapse in the housing market. The lack of stringent regulation and oversight allowed this practice to proliferate, exacerbating the financial crisis that followed.

Conklin et al. (2020) develop a model to understand how appraiser behavior is influenced by a loan officer's preference for favorable appraisals, defined as appraised values aligning with or exceeding contract prices. Their model suggests that during this time appraisers tended to cater to loan officers to enhance their chances of securing future business and that more competitive markets amongst appraisers tended to result in more inflated appraisals. To validate their model, they analyze a sample of purchase mortgages originated by a prominent subprime mortgage lender between 2003 and 2006. The findings indicate that a one standard deviation increase in appraiser competition, measured at the MSA/year level, correlates with a 1.6–3.7 percentage point rise in the prevalence of at-price appraisals. Moreover, this effect was found to be more pronounced in areas witnessing high house price growth.

Kruger and Maturana (2021) identify and measure appraisal inflation in a sample of internal loan data by comparing appraisals to AVM valuations and property purchase prices for years 2001-2007. Based on their analysis, they conclude that non-agency securitized loan appraisals are, on average, 5% higher than AVM valuations, and that appraisals routinely target pre-specified values, resulting in inflated appraisals for half of purchase loans and a similar share of refinance loans. The authors also find that inflated appraisals significantly understate loan-to-value (LTV) ratios and predict delinquency and losses. Calem et al. (2021) provide further insights of mortgage risk in relation to appraisal accuracy by examining appraisal and contract price data alongside mortgage default patterns. Their analysis also reveals the occurrence of appraisals aligning with contract prices rises at loan-to-value boundaries, above which mortgage insurance rates increase as indicated by their model. Furthermore, supporting the notion of information loss or a broader tendency for appraisals to artificially affirm contract prices, the study establishes a correlation between mortgages with appraised values matching contract prices and an increased likelihood of default.

To address these concerns, new regulations were introduced to reduce conflicts of interest and improve the accuracy of property valuations. The HVCC was implemented on May 1, 2009, following a joint agreement between Fannie Mae, Freddie Mac, the Federal Housing Finance Agency, and the New York State Attorney General. Later, key provisions of the HVCC were incorporated into the Dodd-Frank Act of 2010. Under the HVCC, lenders are prohibited from pressuring appraisers to reach a predetermined value for a property, ensuring more independent and unbiased assessments.

Subsequent research finds short-run evidence that HVCC led to reductions in inflated valuations at the time of its initiation. (Shi and Zhang, 2015; Shui and Murthy, 2018; Agarwal et al., 2016; Ding and Nakamura, 2016). However, while the 2009 HVCC and the appraisal-focused reforms in the 2010 Dodd-Frank Act addressed known conflicts of interest between lenders and property appraisers, they did little to change the methods that appraisers use, which result in biased valuations. To design more effective reforms and assess the economy's vulnerability to future crises, it is crucial to gain a deeper understanding of the motivations, mechanisms, and harm caused by appraisal bias (Eriksen et al., 2024).

2.2.2 Comp Selection and Adjustments

Mayer and Nothaft (2022) of appraisals completed in 2015 and 2016 reveals persistent appraisal bias. Their analysis delves into the underlying development of appraisals, uncovering that comparable properties were often valued higher than the subject property. They observe a tendency among appraisers to make relatively small downward adjustments to higher-valued comps while being less likely to adjust downward higher-priced comps. Utilizing a large sample of appraisals for purchase-money loan applications, they find a notable prevalence of selecting more expensive comps, with a strong positive correlation between leverage and the representation of costly comps.

Further analysis of comp price adjustments reveals disparate patterns, where downward adjustments to higher-valued comps are smaller and less responsive to price differences, while upward adjustments to lower-valued comps align more closely with the subject's price difference. Overall, their analysis identifies three key sources of appraisal overvaluation: a selection bias favoring higher-valued comps, a first-order calibration bias toward smaller downward adjustments for higher-valued comps, and a second-order calibration bias in which downward adjustments on higher valued comp sales do not increase as the comp-subject price difference widens, whereas upward comparative adjustments on lower valued comparable sales increase commensurately as the price difference with the subject widens.

Eriksen et al. (2024) construct a detailed property-level dataset comprising appraiser-reported attributes for 4.6 million loan applications from 2013 to 2017 to assess the consistency of these reports. They propose that appraisers may deliberately misreport property attributes to justify inflated valuations, thereby increasing the likelihood of mortgage approvals. By analyzing transactions where the same appraiser provided multiple sets of property attributes within a four-quarter period, they uncover evidence suggesting systematic overvaluation through attribute manipulation. Their analysis reveals widespread strategic misreporting across markets, particularly affecting highly leveraged borrowers. These borrowers, whose appraisals showed inconsistencies, were 9.8% more likely to become seriously delinquent on their loans.

Eriksen et al. (2020) investigate the impact of price awareness on valuation practices, focusing on a subset of residential properties appraised twice within a six-month period, with one appraisal conducted by an appraiser unaware of the contract price. This scenario arises when Fannie Mae owns a property post-foreclosure, commissioning its own appraisal. The "pre-contract" appraisers follow the USPAP methods, documenting property descriptions, and selecting, adjusting, and weighting comparable transactions used to justify their appraised value. A comparison is then made with a "post-contract" appraisal commissioned by a mortgage lender after a loan application. Significantly differing property descriptions and practices were observed for appraisers aware of the contract price. Appraisers aware of contract price were more than twice as likely to appraise at least equal to the contract price, with valuations averaging 4.2% to 8.3% higher than those of appraisers unaware of contract the price.

Conklin et al. (2023) examines the utilization and impact of distressed properties as comps in residential appraisals. The authors first detail the prevalence of their use and assess their relative comparability. Subsequently, they estimate the influence of distressed comps on the appraisal value and explore their effect on the likelihood of appraisals falling below the contract price. Their findings suggest that distressed comps are, on average, suitable matches for subject properties, indicating that they are not merely employed as a last resort. Contrary to expectations, these distressed comps do not adversely affect appraised values, as appraisers adapt and make appropriate adjustments over time. However, the authors do find that the use of distressed comps is associated with a higher probability of a below price appraisal due to the increased spread of appraisals around the contract price, particularly for higher priced homes. Despite this increased uncertainty, the authors emphasize that appraisers learn the appropriate adjustments over time.

Bogin and Shui (2020) find that appraisal bias is notably prevalent in rural areas, with over 25% of rural properties being appraised at more than five percent above the contract price, in contrast to 12.7% in urban areas. This tendency towards upward appraisal bias is particularly accentuated in rural settings due to the scarcity of comparable sales and increased heterogeneity among homes. .

2.2.3 Renegotiation When Below Contract Price

An appraised value below the contract price can negatively impact the real estate market in several ways: the buyer may be forced to make a larger down payment, the seller may have to reduce the agreed-upon sale price, or the sale could be canceled or significantly delayed. Fout and Yao (2016) explore the causes and consequences of appraisals falling below contract prices for appraisals spanning from September 2011 to August 2012. Utilizing a distinctive dataset encompassing appraisals from both subsuquent realized and unrealized sales, they observe that 8.2 percent of all appraisals during this timeframe were 2 percent or more below the contract price. In comparison to appraisals meeting or exceeding the contract price, they find that a low appraisal significantly increases the likelihood of the buyer renegotiating for a better price, escalating from 8 percent to 51 percent. Moreover, the probability of the sale being delayed or canceled rises from 25 percent to 32 percent.

Their findings indicate that low appraisals are influenced by several factors such as a scarcity of available comps, appraisers trailing behind recovering markets and distinctive property characteristics that may pose challenges in accurate evaluation. Across prominent housing markets, they estimate that low appraisals may have potentially caused a modest average decrease of 0.2 percent in home prices and resulted in an average of 0.3 percent fewer purchase transactions over the studied period.

Examining data from loan applications for home purchases, (Fout et al., 2022) explore how buyers respond when the appraised value falls below the contract price, which significantly increases the likelihood of negotiating a lower price. The authors posit that two mechanisms drive the heightened rates of renegotiation. First, they identify a liquidity channel, particularly affecting financially constrained borrowers for whom a low appraisal impacts financing costs. Secondly, for financially unconstrained borrowers, a news channel is recognized, wherein the informational content of the low appraisal alone prompts borrower renegotiation. Importantly, the study demonstrates that low appraisals result in lower renegotiated prices through these channels without substantially reducing the likelihood of a loan application leading to loan origination or significantly extending the time from contract signing to sale. The findings contribute to the literature by suggesting that low appraisals entail a relatively modest cost to lenders or real estate brokers in terms of foregone business.

Shui and Murthy (2019) study whether first-time homebuyers overpay for their homes and whether the magnitude of the overpayment varies with the diligence of appraisers involved. They present a robust result that first-time homebuyers sort into smaller and cheaper houses, but that once observed and unobserved house characteristics are controlled for, they pay a premium compared to their more experienced counterparts. Their analysis additionally suggests that certain appraisals and appraisers might be able to mitigate this overpayment by inducing downward renegotiation.

3 Data Sources

3.1 Federal Housing Financing Agency

3.1.1 Uniform Appraisal Dataset: Appraisal-Level Public Use File

Released by the Federal Housing Financing Agency (FHFA), the Uniform Appraisal Dataset (UAD) Appraisal-Level Public Use File (APUF) is the nation's first publicly available appraisal-level dataset of appraisal records, giving the public new access to a selected set of data fields found in appraisal reports. The UAD APUF is based on a five percent nationally representative random sample of appraisals for arm-length single-family mortgages acquired by the Fannie Mae and Freddie Mac Enterprises. The dataset comprises appraisals carried out using the Fannie Mae Form 1004/Freddie Mac Form 70, excluding assessments for condominiums, manufactured housing, properties with two or more units, single-family investment properties, and partial appraisals. The current release includes appraisals from 2013 through 2021 and includes state, county, and 2010 census tract definitions. [5]

In 2022, the FHFA also released another a novel appraisal database, the UAD Aggregate Statistics Data File. This database utilizes appraisals spanning from 2013 to the most recent quarter includes aggregate statistics based on all (i.e., 100 percent) of eligible UAD appraisal records. While this dataset is based on all eligible appraisals, it lacks the detailed insights that are available in the PUF appraisal-level dataset. In this study, I use the Aggregate Statistics Data File to analyses trends post 2021 and to better capture the density of appraisals during the Covid-19 pandemic.

This paper utilizes the APUF dataset for estimation. The APUF records includes information about the subject property and information about one or more comparable properties used to estimate value. Information about the subject property includes details such as; contract price, appraised value, number of bedrooms, number of bathrooms, gross living area and measures of quality of the subject property. Information about the comparable properties include details such as; the number of comps used, average dollar adjustments and its proximity to the subject property. In addition, information on the appraiser's opinion concerning local property value trends, marketing time and information on housing supply and demand trends. Table 1 presents summary statistics of key variables used in this analysis.

3.1.2 Home Price Index

I use data from the FHFA which report home price indices (HPI) at the Census tract level. The FHFA HPI is a broad measure of the movement of single-family house prices. The HPI is a weighted, repeat-sales index, meaning that it measures average price changes in repeat sales on the same properties within Census tracts which adjusts for the quality over time (Calhoun, 1996). [6]This information is obtained from repeat mortgage transactions on single-family properties whose

[5]One limitation of these data is that I only observe appraisals associated with successfully originated loans introducing potential sample selection biases.

[6]The index employs a weighting procedure that allows for greater sampling variability in the price appreciation for houses that experience a longer time between transactions. As noted in Calhoun (1996), given two identical properties,

mortgages have been purchased or securitized by Fannie Mae or Freddie Mac.

FHFA HPIs are based on data for a sample of houses with conforming mortgages, that is, mortgages below certain cut-off house values and loan-to-value ratios and that, in addition to sales prices, observations obtained from homes that were refinanced are used in constructing the index. Jumbo loans-mortgages that exceeds the limits set by the FHFA are not eligible to be purchased, guaranteed, or securitized by Fannie Mae or Freddie Mac. If the imputed market value of homes grow to exceed the conforming limit they are not excluded from the sample since the conforming limit is based on the mortgage balance of the home and not its imputed market value. Loan limit increases reflect the year-over-year percentage change in the FHFA HPI for the United States and are based on the third quarter. [7] The FHFA HPI serves as a timely, accurate indicator of house price trends at various geographic levels. The key advantage of the FHFA HPIs is that they are available at the Census tract level for most of the United States over a long sample period. House price index data are missing for tracts where there are insufficient repeat sales within a tract to get an accurate estimate of house price trends for that tract.

3.2 American Community Survey

I use these data in conjunction with data from IPUMS National Historical Geographic Information System which provides summary statistics and GIS files for U.S. censuses and other nationwide surveys at the Census tract level (Manson et al., 2023). In particular, I use American Community Survey 5-year estimates for the years 2015-2019 to control for local demographics and housing market features.

3.3 SafeGraph

Last, I use data on consumer spending behavior at specific points of interest (POIs) from SafeGraph. The Spend dataset aggregates anonymized debit and credit card transaction data for individual places in the U.S. on a monthly basis, dating back to January 2019. This dataset includes spending information for over 10 million customers at more than 1.1 million POIs across 5,454 brands. When aggregated to the parent brand level, SafeGraph's Spend data can be compared with financial indicators, such as quarterly revenue, to serve as a benchmark for validation. [8]SafeGraph also assesses geographic representativeness by comparing its state-by-state customer home location data to the true proportions reported by the 2019 U.S. Census. SafeGraph's panel density

differential rates of appreciation, change in the neighborhood socio-demographics and other idiosyncratic deviations from market-level mean appreciation are more liable to arise the longer the time between transactions. This motivates using a generalized least squares weighting procedure in which the variance in house price appreciation is quadratic in the time between consecutive transactions for a given property.

[7]Freddie Mac and Fannie Mae are government sponsored enterprises chartered by Congress to provide a secondary market in conventional mortgages and increase lending for home ownership. These data include mortgage records for single-family, single-unit, detached properties, excluding condominiums, cooperatives, and planned urban developments. Mortgage transactions on properties financed by government insured loans, and properties financed by mortgages exceeding the conforming loan limits by Freddie Mac or Fannie Mae are excluded. As of 2024, the conforming limit in expensive coastal markets is a loan value of $1,0149,825 and the maximum LTV is 97%. The conforming limit is $766,550 in the least expensive housing markets.

[8]Based on one such analysis, SafeGraph data track with quarterly revenue from major brands like McDonald's, Chipotle, and Target, including cases where companies report online sales separately than overall revenue (e.g., Chipotle).

closely mirrors actual population density, with an average percentage point difference of less than 1% and a maximum variation of +/-4% per state.

4 The Monocentric City Model

4.1 Interpretive Framework

To interpret the home appraisal data, I consider the WFH shock in a canonical urban model of housing in cities in the tradition of (Alonso, 1964; Muth, 1969; Mills, 1967) as presented in (Duranton and Puga, 2014, 2015; Duranton and Handbury, 2023) to explain the evolution of the housing market over first two years of the Covid-19 Pandemic. I assume that there is no movement in and out of the city. That is, the city is 'closed.' To a first approximation, this assumption is consistent with what we observed during the first two years of Covid (Ramani and Bloom, 2021; Duranton and Handbury, 2023). Flows of migrants between cities were small and WFH does not in most cases allow residents to relocate anywhere they would want to. They still needed to get to their job, at least some of the time.

Preferences can be represented by a utility function $U(A,\ u(h,z))$ written in terms of the common amenity level enjoyed by everyone in the city, A, and a sub-utility $u(h,z)$ derived from individual consumption of housing, h, and of the numẽraire, z. Commuting cost increase linearly with distance to the CBD, so that a worker living at distance, x from the CBD, incurs a commuting cost τx. This leaves $w - \tau x$ for expenditure on housing and the numẽraire, where w is the wage.

Denoting by $P(x)$ the rental price of housing at a distance x from the CBD, we can use the dual representation of the utility derived from housing and the numẽraire, and represent preferences with

$$U(A, v(P(x), w - \tau x)), \tag{1}$$

where $\frac{\partial U}{\partial A} > 0$, $\frac{\partial U}{\partial v} > 0$, $\frac{\partial v}{\partial P(x)} < 0$, and $\frac{\partial v}{\partial (w-\tau x)} > 0$. All residents in the city are identical in income and preferences, enjoy a common amenity level, and are freely mobile within the city. At the residential equilibrium, residents must derive the same sub-utility from housing consumption and the numẽraire

$$v(P(x), w - \tau x) = \bar{v} \tag{2}$$

Totally differentiating Equation 2 with respect to x yields

$$\frac{\partial v(P(x), w - \tau x)}{\partial P(x)} \frac{\mathrm{d}P(x)}{\mathrm{d}x} - \tau \frac{\partial v(P(x), w - \tau x)}{\partial (w - \tau x)} = 0, \tag{3}$$

which implies

$$\frac{\mathrm{d}P(x)}{\mathrm{d}x} = -\frac{\tau}{-\frac{\partial v(P(x), w-\tau x)}{\partial P(x)} / \frac{\partial v(P(x), w-\tau x)}{\partial (w-\tau x)}} = -\frac{\tau}{h(x)} < 0, \tag{4}$$

where the simplification follows from an application of the envelope theorem (Roy's identity). Equation 4 is often referred to as the Alonso-Muth condition. It states that, at the residential equilibrium, if a resident moves marginally away from the CBD, the cost of her current housing consumption falls just as much as her commuting costs increase. Thus, the price of housing decreases with distance to the CBD. Then, residents react to this lower price by consuming more housing (larger residences) the farther they live from the CBD. To see this, simply differentiate the Hicksian demand for housing with respect to x

$$\frac{\partial h(P(x),\bar{v})}{\partial x}=\frac{\partial h(P(x),\bar{v})}{\partial P(x)}\frac{\mathrm{d}P(x)}{\mathrm{d}x}\geq 0. \tag{5}$$

Note, this is a pure substitution effect, since utility is being held constant at $\bar{v}$. This also implies that the price of housing is convex in distance to the CBD; house prices do not need to fall as fast as commuting costs increase with distance to the CBD to keep city residents indifferent, since they enjoy having a larger house.

4.2 The Commuting Dividend and Home Office Tax

As discussed in Duranton and Handbury (2023), people that WFH do not need to commute to work as frequently and, therefore, face lower average commuting costs. The effect of lower commuting costs following from WFH is most directly apparent in Equation 4. A lower cost of commuting τ flattens the housing price gradient through a direct effect on the numerator in Equation 4. With lower commuting costs, housing closer to the urban fringe enjoys cheaper access to downtown and its price increases. Housing closer to downtown now offers a smaller accessibility advantage and its price goes down.

Because the city remains "closed" to new residents for now, a lower cost of commuting also implies an income effect whereby residents all enjoy a higher disposable income after spending less on commuting. In turn, a higher disposable income implies a greater demand for both housing and the other good. Because housing is, in the short-run, in fixed supply at each location, its price increases. Lower commuting costs provide a parsimonious explanation for the changes described above. With a constant population and a constant stock of housing, the city-level average housing consumption is unchanged but the housing price gradient shifts: housing costs decrease in the city center and increase in the suburbs. These patterns are consistent with the short-run price response to the WFH shock in the first year of the pandemic, when urban expansion was indeed limited.

At the same time, moving the office inside the home implies devoting part of what was a resident's living space to a home office. When working from home, the place you work might be more convenient but it still takes space. It is as if housing space at home is taxed. This "tax" can be considered proportional to the size of the house. Hence, this tax is equivalent to an increase in the price of effective housing for which demand will decline. The first effect of the home-office tax is thus to reduce housing available for enjoyment. If the price elasticity of the demand for effective housing is below one (inelastic), demand for total housing will actually increase further with the home-office tax. The literature is not definitive on the price elasticity of housing demand. If demand for housing is instead modestly inelastic, as suggested in (Hanushek and Quigley, 1980), and supply is fixed, then the effect of the WFH dividend will be amplified by higher prices.

4.3 Appraisal Data Insights In Context of The Model

I now explore mechanisms that may have led the 128% increase in appraisals below contract price (BCP) since 2019 for the 12 largest cities through the lens of the monocentric city model. Figure 2 plots the share of appraisals BCP form the year 2017 to 2023 by their distance to the CBD using the UAD aggregate statistics dataset. For the purpose of this analysis, I define City Hall as the center point of the Central Business District and census tracts that are within 1.75 miles of the center point as included in the CBD. From 2017 to 2019 the difference in the percent of BCP appraisals for the CBD and appraisals from a distance of ten miles or more within the same metropolitan area was roughy 3% over this time. Once the Covid-19 pandemic started in 2020 and residents begin to work from home and flee the city center, this difference between the two distance measures began to spike. This difference roughly doubled to 6% in 2020 and grew to a staggering 11% in 2021, more than tripling the 2017-2019 average. This percent change is mainly due to the increase in the percent of below contract price appraisals in census tracts that are over ten miles away from the CBD. For the CBD, the BCP percentages remained roughly constant over this time relative to suburban areas.

Panel A and Panel B of Figure 3 plot the distribution of the home appraisal to contract price ratio for appraised homes within the CBD and for homes 10 miles or more from the CBD respectively. For each panel, the dark shade distributions reports data for the year 2021 and the white distribution reports the 2017-2019 average. In 2021 a larger share of appraisals matched the contract price for homes within the CBD and a larger share appraised below contract price in areas that are more than ten miles away from City Hall.

Prices have historically been higher in the CBD and decrease with distance to the CBD as noted in prior research and in the model outlined in this section. This trend in housing demand suddenly reversed during the onset of Covid-19 and it appears that appraisers didn't capture the full extent of this shift in housing demand. For each appraisal, the APUF data file records information on how the appraiser "judged" the "market temperature" in the local area of the subject property based on measures such as; the specified typical length of time a property would stay on the market before being sold in the neighborhood, the local property value trends in which the appraiser specified the trend of one-unit property values in the subject's neighborhood and trends concerning housing demand versus housing supply in the neighborhood. Figure 4 plot these trend measures overtime by distance to the CBD.

Panel A of Figure 4 show appraiser specified local property value trends. Prior to the year 2020 roughly 80 % of the appraisals were reported as having stable home prices which varied little by distance to the CBD. However, somewhat surprisingly, for the year 2020 the trend remained constant even though home prices rose considerably, especially in areas further away from the CBD. In 2021, noticeable adjustments began to emerge and appraisers seemed to internalize the change with respect to distance to the CBD. However, reported home price trends in the CBD saw an increase in the share being reported as "increasing" even though this is not what the data, previous research and economic theory seem to suggests. Similar trends are found in Panel B and Panel C with respect to marketing time and demand/supply conditions respectively.

Overall, Figure 4 seems to suggest that appraisers' judgement of the housing market temperature somewhat lagged the sudden housing demand shock but they gradually gained insights of the spatially concentrated change in housing demand. Figure 5 show the trends in consumer spending as measured by SafeGraph's mobility data. The CBDs for the 12 largest cities saw the largest decrease in consumer spending during Covid-19. The areas further away from the CBD saw a significant yet relatively smaller decrease and show signs of remaining more stable potentially due to the increase in residences moving further away from the CBD as the WFH shift became common.

5 A Conceptual Framework of Property Value Estimation

5.1 Market Value vs. Transaction Price vs. Appraised Value

5.1.1 Market Value and Transaction Price

The primary task of a home appraiser is to produce the best possible estimate of the market value of a subject property. As discussed in (Geltner, 1997; Geltner and Ling, 2006; Geltner et al., 2014) and expounded upon here, in private real estate markets, market values are not directly observable to the appraiser, however, this does not mean they don't exist. A key distinction between real estate and securities is that property markets involve the exchange of unique, indivisible assets, along with the responsibilities for their governance and operations. This introduces a degree of "lumpiness" in the market, making it challenging to pinpoint the precise market value of any given asset at any moment. The greater the uniqueness of the assets and investors involved, the harder it becomes to accurately estimate market values. Conversely, when assets and investors are more homogeneous, estimating market values becomes easier.

In real estate, market value represents the expected price at which an asset can be sold under current market conditions. It reflects the ex-ante expectation, or the mean of the probability distribution, of possible prices—the most likely price at which a deal will be struck between two parties before the transaction occurs. However, price variation is influenced by factors beyond market fundamentals. When listing a property for sale, the contract price is uncertain and depends partly on the buyer encountered. For instance, a particularly enthusiastic buyer may offer a higher price, while a tough negotiator could push for a lower one.

Other influencing factors include; seasonality, distress sales like foreclosures (REOs) and short sales, as well as seller concessions or credits at closing. Financing arrangements, such as who pays the loan points, also contribute to price differences. Additionally, changes in credit access and broader market conditions can affect prices. Events like death or estate sales, especially when multiple heirs are involved, can further impact pricing dynamics (Geltner et al., 2014). In a highly liquid, dense market where homogeneous assets are frequently traded by many buyers and sellers—such as in the stock market—market value typically aligns closely with the actual transaction price. In these environments, market values represent market-clearing prices, where supply and demand are balanced for uniform, divisible assets. In real estate markets, both parties in a deal may have thoroughly done proper research and made full, reasonable use of all the information and resources available at the time of the transaction, yet one side can still end up with a better deal than the other. However, such differences on both the positive and negative side tend to average out over the long run and across many deals.

To understand these fundamental points, Figure 6 shows the overlapping distribution of potential buyers and sellers reservation prices within a population of properties at a given point in time. The horizontal axis refers to the reservation values, the prices at which they will stop looking any further for a willing partner and will agree to trade. The height of the curves along the vertical axis indicates how many potential market participants place that reservation value on the property. Thus, for any given price on the horizontal axis, we would have a number of willing buyers equal to the area underneath the buyer curve to the right of the given price, and we would have a number of willing sellers equal to the area underneath the seller curve to the left of the given price.

Figure 6 indicates that transactions in this market may occur in the overlapping gray shaded region where some buyers will have reservation prices at least as high as the reservation prices of some sellers. These prices will tend to be distributed around a value labeled "MV" which can be described as the conceptual market value of the population of residential properties. We can think of the value MV as representing the "true" value as of a given point in time, with MV being unobservable empirically. All we can observe are valuations drawn from the probability distribution around MV. If the empirical observations are actual transaction prices, the direct and fundamental indication of market value, then the difference between any given price observation and the unobservable true market value is referred to as "transaction price noise," or "transaction price error". By definition, this error will be unbiased (equally likely of being on the high side or the low side), as long as we assume all the transaction price observations occur at the same time.

5.1.2 Appraised Value

Another important type of empirical value indication for properties are appraisals made by professional real estate appraisers. But appraisals are only estimates of value, based themselves more fundamentally on transaction price indications (comps). Hence, both transaction prices and appraised values contain "error" relative to the "true" market value of the properties. Similar to transaction prices, property appraisals are also dispersed cross-sectionally around true market values as of any given point in time. The difference between a given empirical appraised value and the market value is called "appraisal error", although there is no implications that the appraiser has exhibited any incompetence, negligence, or impropriety (Geltner et al., 2014). Although appraised values are dispersed around the underlying true values, unlike transaction prices the appraised-value dispersion is not necessarily centered on the true value. In other words, appraised values may be biased as of any given time. Such bias may result from very rational and proper professional practices on the part of the appraiser, given the nature of the empirical information available in the real estate market.

This source of bias steams from the fact that appraised values tend to lag in time behind true contemporaneous market values. This is referred to as "temporal lag bias", yet this more precise but temporally biased estimate will provide you with more solid historical evidence explicitly documenting the estimated value of your particular property. It will do this by using more sales comps for the subject property that in the appraiser's judgement are particularly similar to the subject property.

The selection of comps are supposed to be very similar to the subject property and whose differences from the subject property are scrutinized and carefully considered as described in Section 2. This approach considers unique, idiosyncratic features of the subject property, eliminating the most important potential source of purely random error. But the trade-off is that such comps are scarce in time, and the appraiser must therefore reach back relatively far in time. If the appraiser ignored all past value indications and considered only transactions that have occurred say, within the past month, no matter how far removed or different from the subject property these transactions were, and no matter how few such transactions were, such an appraisal would likely not be very accurate for the specific subject property being appraised.

In short, error falls fundamentally into two major categories: purely random error (also know as noise) and temporal lag bias. Furthermore, in trying to design an optimal value estimation technique, there tends to be a natural trade-off between these two types of error. It is hard to reduce random error without increasing the lag bias, and it is hard to reduce the lag bias without increasing the random error. The following section presents a simple theoretical model of property value estimation to shed further insights into this concept and its relation to the WFH housing demand shock. I subsequently present insights from FHFA appraisal data within the framework of the model.

5.2 A Stylized Model

Geltner and Ling (2006) present simple stylized model of the property value estimation process. The objective of this process is to estimate the market value of a specified population of properties or, equivalently, the market value of a representative property within that population, as of each period of time, t, in which I focus on the latter. The true market value of a subject property is defined as V_t. Suppose that within each period of time, n properties are sold with observable transaction prices. These transaction prices are labeled $P_{i,t}$, for i = 1 to n. For illustrative purposes, I assume that t is indexed in months. The model assumes that each transacting property is an equally valid representative of the type or class of properties in the population of interest. As described in the preceding section, these n observable transaction prices are dispersed randomly around the true market value

$$P_{i,t} = V_t + \epsilon_{it}, \tag{6}$$

where ϵ_{it} is the random error or "noise" term, which is iid normal with zero mean and standard deviation σ_ϵ.

Consider the arithmetic average across N of the transaction prices starting with transactions that are among the n that occur within period t. This estimator is $\hat{V}_t(N)$

$$\hat{V}_t(N) = \frac{1}{N}\sum_{i=1}^{N} P_{i,t}, \tag{7}$$

and contains a purely random standard error of $\frac{\sigma_\epsilon}{\sqrt{N}}$. Notice that the purely random error (or "noise") component in the market value estimate is reduced by an increase in the sample size. If the N transaction observations all occur with month t (which is only possible if $N \leq n$), then $\hat{V}_t(N)$ will also have a mean of V_t. In this case, $\hat{V}_t(N)$ will be an unbiased estimator of the period t market value of the property.

However, if the sample size N is greater than n -the number of transaction observations in any one month t- the random error magnitude of the estimator will still equal $\frac{\sigma_\epsilon}{\sqrt{N}}$, but the mean will no longer be V_t. Some of the N transaction price observations will have to be drawn from one or more earlier months in time. This will cause the mean of $\hat{V}_t(N)$ to be some average of V_t and previous market values of the property population: V_{t-1}, V_{t-2} or perhaps, V_{t-7}. This will introduce temporal lag bias into the $\hat{V}_t(N)$ estimator.

Given a population transaction density of n per month, the appraiser's problem is to determine the choice of N so as to develop the estimate of V_t. Clearly there is a trade-off between the two types of error that will exist in the estimates. The larger the N, the smaller will be the purely random error whose magnitude is: $\frac{\sigma_\epsilon}{\sqrt{N}}$. However, increasing N beyond n will add temporal lag bias. The ratio $\frac{N}{n}$ determines how far back in time to reach for the estimation sample. If N=$2n$, the transaction observations are drawn from two months in time, t and $t-1$. To simplify the analysis, assume a sample size would never be chosen that is less than a whole multiple of n. That is, if the decision is to go back to a given period of time in order to increase the transaction sample size, all transactions within that period will be included. Thus, the ratio $\frac{N}{n}$ will be an integer, and the maximum lag in the estimation sample, L, will be one less than the $\frac{N}{n}$ ratio: $L = \frac{N}{n} - 1$. The general expectation of $\hat{V}_t(N)$ can now be specified as

$$\mathbb{E}(\hat{V}_t(N)) = \frac{1}{N/n} \sum_{s=0}^{\frac{N}{n}-1} V_{t-s} = \frac{1}{L+1} \sum_{s=0}^{L} V_{t-s}. \tag{8}$$

.

To solve for the optimal sample size, Geltner and Ling (2006) proposes to minimize the mean squared error (MSE) in the estimate, where the error is the total error, including both the random noise and the lag bias. That is, N is selected (or equivalently L) so as to minimize the expectation

$$\begin{aligned} MSE &= \mathbb{E}((\hat{V}_t(N) - V_t)^2) \\ &= \mathbb{E}[(\frac{1}{N}(\sum_{i=1}^{n}(P_{i,t} - V_t) + \sum_{i=n+1}^{2n}(P_{i,t-1} - V_t) + ... + \sum_{i=N-n+1}^{N}(P_{i,t-L} - V_t))^2] \\ &= \frac{1}{N^2}(\underbrace{\sum_{i=1}^{N} \epsilon_i^2}_{\text{Variance}} + \underbrace{n^2 \sum_{i=1}^{L}(V_{t-s} - V_t)^2)}_{Bias^2}. \end{aligned} \tag{9}$$

If for illustrative purposes, the true market value follow a random walk $V_t = V_{t-1} + r_t$ where r_t is iid with zero mean, and the true market volatility is σ_r, Geltner and Ling (2006) show that the objective function simplifies to

$$\begin{aligned} MSE &= \frac{VAR(\epsilon_i)}{N} + \frac{n^2 VAR(r_t)}{N^2} \sum_{s=1}^{\frac{N}{n}-1} s^2 = \frac{\sigma^2}{N} + \frac{n^2 \sigma_r^2}{N^2} \sum_{s=1}^{\frac{N}{n}-1} s^2 \\ &= \underbrace{\frac{\sigma_\epsilon^2}{n(L+1)}}_{\text{Random Error Effect}} + \underbrace{\frac{\sigma_r^2}{(L+1)^2} \sum_{s=1}^{L} s^2}_{\text{Lag Bias Error Effect}}. \end{aligned} \tag{10}$$

Thus the MSE consists of two terms. The first term on the right hand side (RHS) of Equation 10 is the purely random error effect, which consists of the cross-sectional price dispersion variance σ_ϵ^2 times a "noise factor," $\frac{1}{n(L+1)}$, that is diminishing in the number of lags. The second term on the RHS of Equation 10 is the las bias error effect. It is the true market return volatility (squared) time a "lag factor," which is the sum of the squared lags divided by $(L+1)^2$.

The objective is to find the value of L that minimizes the MSE. The noise factor in the overall error diminishes with every increment in L and more so the larger is n, the transaction density per period. If purely random error were the only type of error, all available comps should be sued by the appraiser to estimate the current value of V_t However, the lag factor component in the overall error term increases with each increment in L, thus presenting a trade-off. As lags are added, the noise factor is reduced by a diminishing increment, while the lag factor in the MSE is increased by an increasing increment. Thus, if the MSE is not already minimized at L = 0, then it will be minimized at some finite value of L as we step up through the integers: L = 1, 2, . . . n.

Geltner and Ling (2006) show that the optimal lag can be characterized by examining the finite differential of the MSE as a function of L and setting this incremental error equal to zero to generate the following optimal lag criterion

$$\frac{\Delta MSE}{\Delta L} = \left[\frac{\sum_{s=1}^{L+1} s^2}{L+2} - \frac{\sum_{s=1}^{L+1} s^2}{L+1}\right]\sigma_r^2 - \left[\frac{1}{n(L+1)(L+2)}\right]\sigma_\epsilon^2 = 0. \tag{11}$$

Further simplifying Equation 11 leads to,

$$\frac{\Delta MSE}{\Delta L} = \left[\frac{\sum_{s=1}^{L+1} s^2}{L+2} - \frac{\sum_{s=1}^{L+1} s^2}{L+1}\right](L+1)(L+2) = \frac{\sigma_\epsilon^2}{n\sigma_r^2}. \tag{12}$$

The optimal lag is an increasing function of the price dispersion σ_ϵ, and a decreasing function of both the transaction density n and the market return volatility σ_r. The model also shows that the optimal lag is a function only of the $ratio$ of the two dispersion parameters, cross-sectional divided by longitudinal standard deviation and not of the absolute values of these parameters individually.

To summarize graphically, Figure 7 shows the Noise vs. Lag Trade-off Frontier. The two axes represent the two types of error, arranged so that the farther out from the origin, the less the error. The horizontal axes represents greater precision in the value estimate, that is, less purely random error. Points farther to the right of the axis have less noise. The vertical axis represents greater "currentness", or less temporal lag bias. The farther up you go along the axis, the more availability of comps that sold closer in time to the subject property. The thick solid concave curve represents the frontier, as provided essentially by the sample size of properties (N). Points outside of the frontier are not feasible. The frontier would shift outward due to an increase in the sample size, recalling that N = (L +1)n.

The convex curves are indifferences curves of constant utility, from the perspective of the users of the appraisal information. As users of property value estimates dislike both random-error and lag bias, indifference curves that are farther up and to the right (farther "northeast") represent higher levels of utility: $U_1 < U_2 < U_3$. The indifference curves are convex because of declining marginal utility of either sort of accuracy. Once a relatively high level of precision is obtained, it is more useful to reduce any significant lag bias in the value estimate than to add another increment to the already high precision of the value estimate. Similarly, once the index is quite up to date, it is more useful to reduce any significant noise in the value estimate than to reduce the lag bias by another increment.

The exact shape and slope of the indifference curves will depend on the user and the use of the property-value estimation. (Geltner and Ling, 2006; Geltner et al., 2014) express that most users of individual (disaggregate) property appraisal place a higher premium on precision. This would be reflected by a utility function with relatively steep indifference curve as shown in the diagram. On the other hand, many users of aggregate appraisals(such as to construct an index tracking a population of properties) may care more about avoiding bias since lower precision will diminish due to the larger sample size, $\frac{\sigma_\epsilon}{\sqrt{N}}$. The optimal balance between lag bias and random error is found at the point where the trade-off frontier is tangent to the indifference curve, at the point labeled A.

5.3 Insights From Appraisal Data

Having established a theoretical framework, in this subsection I examine the home appraisal data in light of the model. As noted previously, the noise factor in the overall error diminishes with the transaction density per period (larger n). Figure 8 plots the average of the contract price and appraised value difference for a given census tract as a function of the total number of appraisals in that census tract for the year 2021. This contract price and appraised value spread is measured using the UAD APUF data set while the total number of appraisals is measured using the UAD aggregated statistics data set given that it's not based on a 5% sample. Figure 8 reveals a striking systematic pattern, appraised values tended to deviate further away from the contract price as the density of appraisals (n) deceased within a given census tract. This pattern is consistent with the theoretical prediction highlighted above. As more homes sold within a census tract the difference converges rapidly towards 0. This patterns suggests that appraisal accuracy was highly effected by the density of transactions within a given census tract during the hight of the WFH housing demand increase.

As outlined in the model, the second source of bias that the model predicts is the temporal lag bias. Even though the random error decreases as L increases as highlighted in Figure 8, the lag factor component in the overall error term increases with each increment in L, which is a function of n, highlighting the trade-off. One short coming of this study is that I do not directly observe the transaction date of comps used for the appraisal of the subject property. Yet, as noted in the stylized model of this section and in previous literature, when home prices are rapidly rising in a local area, comps further backed in time generates a lag bias. In such a case one would expect that for similar types of homes, an appraisal that uses relatively more comps will increase the likelihood of using comps that are further back in time (t).

Figure 9 shows the density plots of the contract price and appraised value spread. The solid distribution plots the contract and appraised value difference for the subject properties that use 4 comps to conduct the appraisal and the dashed distribution plots the spread for when "7 or more" comps were used.[9] Another striking pattern emerges, consistent with the predictions of the model, homes appraised using 7 or more comps tended to come in below contract price more often relative to homes appraised using 4 comps. This reflects the temporal lag bias effect when using more comps to appraise subject properties, particularly more so in hot markets.

Figure 9 adjusts for potential neighborhood factors by only plotting the spread for subject properties where all the comps used were within the same census tract as the subject property. Also, Figure 9 also adjusts for sample size differences that may effect the shape of the distribution. To adjust for this difference, I randomly select 36% of the sample of subject properties that were appraised using 4 comps to equate it with the 7 or more sample.[10] Figure 9 also highlights the fact that this difference is not being driven by a lack of comparable properties. Meaning that, the model outlined above would suggest that properties that are "unique" would tend to have fewer comps to select from when appraising the subject property and lead to more dispersion in the contract price and appraised value spread. The two densities tract each other almost identically as one moves

[9] The UAD PUF dataset is top-coded at 7 for the number of comps used.

[10] Roughly 2,700 appraisals are used for each category after this adjustment. Again, note that the APUF dataset is a five percent representative sample.

from left to right on the horizontal axis until the contract price and appraised value difference approaches 0. A clear deviation then emerges in which appraisals that use 7 or more comes see a higher share of contract prices that are above the appraised value. This would suggest that the difference observed is reflective of the temporal lag bias effect.

Panel A of Figure 10 plots the average number of comps used over time by distance to the CBD. On average appraisers tended to use roughly five comps for each appraisal consistently over time and with respect to distance. Using the same amount of comps over time, in theory would have increased the likelihood of using a "stale" comp when housing demand increased during the onset of the pandemic. As mentioned in Section 2, appraiser are required to make adjustments to comps in order to reflect the differences in structural characteristics, neighborhood differences and market conditions. Panel B of Figure 10 plots the average dollar value of comps adjustments made by apprisers over time by distance to the CBD. Some what surprising, on average, apprisers tended to make slight downward adjustments to comps over time throughout the sample, suggesting that the comps used tended to be more expensive than the subject property. In 2021, subject properties appraised in locations over ten miles away from the CBD tended to see slight upward adjustments in comps values.

6 Estimation Results

I now turn to the regression analysis to estimate the $SPREAD$, defined as the difference between the contract price and appraised value of the subject property. I also estimate the probability of an appraisal coming in BCP. All estimation results are for the 12 largest U.S. metropolitan areas. My key independent variables are distance measured dummy variables measuring how far the appraised subject property is from the CBD. More formally, my main regression specification takes the following form

$$SPREAD_{ijt} = \beta_0 + \beta_1 Distance + \mathbf{X}_{ij} + \delta_i + \omega_j + \lambda_t + \epsilon_{ijt}, \tag{13}$$

where i indexes tracts, j indexes MSA and $\mathbf{X}$ denotes the vector of controls. I use data from the APUF to control for the appraisal characteristics of the subject property. Specifically I control for all of the summary statistics variables reported in the Table 1. I also use ACS 2015-2019 5-year estimates data to control for initial Census tract level demographic characteristics before the onset of the Covid-19 pandemic. Specifically, I control for the population density, the share of people with at least a bachelors degree, median household income, homeownership rates and rental prices. I control for both city and tract level fixed effects and a time effect. All standard errors are clustered at the tract level. My Probit specification follows the form of Equation 13 but replaces the dependent variable with an indicator function of whether the appraised value of subject property i in city j, at time t came in BCP.

Table 2 and Table 3 report two-year sample and one-year sample $SPREAD$ estimates respectively. Column1 through Column 3 of Table 2 report estimates for the combined sample years 2018 and 2019 adjusting for various control variables and Column 4 through Column 6 report estimates for the combined sample years 2020 and 2021, likewise adjusting for various control variables. Each distance measure estimate is in reference to census tracts that are just outside the CBD yet within 5 miles of the center point of the CBD (City Hall).

Table 2 reveals that before the onset of the Covid-19 Pandemic, homes appraised in neighborhoods that are more than ten miles from City Hall tended to have larger contract price and appraised value difference. During the 2020-2021 housing demand shock, the difference increased by roughly $800 when comparing specification years that include controls. Also note that the variance of these estimates are smaller relative to the 2018-19 estimates, indicating more precise estimates. Homes appraised in the CBD reveal negative coefficients but are not statistically significant in any reported specification and show signs of a high variance relative to their point estimates. Table 3 report one-year estimates concerning the same outcome of interest. A similar pattern emerges, in 2019, homes appraised further away from City Hall tended to have larger contract price and appraised value difference. Comparing Column 2 and Column 6 the spread increased for homes appraised over ten miles out from City Hall by roughly $3,000 in 2021 coinciding with a greater statistical significance.

Table 4 and Table 5 reports the estimates for the probability of an appraisal coming in BCP. For Column 1 through Column 3 of Table 4, in the 2018-2019 sample, homes ten or more miles from City Hall were only slightly more likely to be below contract price for the specification that includes the full set of controls. Column 3 reports marginal effects of appraisals being 2% more likely of appraising below contract price. Homes within the CBD tended to be 5% more less likely to appraise below contract price but this pattern vanishes for the 2020-2021 sample. Consistent with estimates reported in Table 2, homes more than ten miles from City Hall were roughly 8% more likely to appraise below contract price. Table 5 report the one-year probability estimates. Overall, marginal effects for the year 2019 tend to be weak and/or insignificant. Column 4 and Column 5 reveal a clear jump in this probability for homes in the suburbs for the year 2021, exactly where housing demand increased the most during this time. Homes appraised over ten miles out were roughly 14% more likely to be below contract price.

Overall, the estimation results reported in Table 2 through Table 5, suggest that before onset of the Covid-19 pandemic, homes in the suburbs tended to slightly appraise below contract price more often, although with a higher degree of variance in the estimates. During the shift to WFH, a clear jump in the probability of appraising below contract price in the suburbs emerges along with an increase in the contract price and appraised value difference both measured with higher precision. A limitation of this study is that I only observe appraisals associated with successfully originated loans introducing potential sample selection biases. Loan applications for which the buyer and seller fail to renegotiate due to larger differences in the contract price and appraised value are not observed in my sample. My results therefore can be interpreted as a lower bound of the true effect.

6.1 Discussion and Additional Housing Demand Insights

Gaining insight into the trajectory of housing demand is a top priority for appraisers. The future path of demand may depend critically on the path of remote work. If remote work reverses, then there may be a general reversal in housing demand and potentially house prices. Monte et al. (2023) document that although most cities experienced similar reductions in CBD trips during the pandemic, trips in the largest cities have stabilized at levels that are only about 60% of pre-pandemic levels. In contrast, smaller cities have, on average, returned to pre-pandemic levels. The authors show how the coordination of agents in a city can lead to multiple stationary equilibria dependent on the interdependence of factors such as the productivity of remote work relative to in-person work and the general level of congestion in commuting for each city. The authors show how temporary shocks to the number of commuters (i.e. a lockdown) can permanently affect the structure of cities by selecting a different stationary equilibrium.

Also, prior research documents how the trajectory of housing demand evolves in a systematic way when there is a housing demand shock. Initially low price neighborhoods within a city appreciate more than initially high price neighborhoods during citywide housing booms. Guerrieri et al. (2013) present a model which links house price movements across neighborhoods within a city and the gentrification of those neighborhoods in response to a city wide housing demand shock. A key ingredient of the model is a positive neighborhood externality: individuals like to live next to richer neighbors. The in-migration of the richer residents into these border neighborhoods will bid up prices in those neighborhoods causing the original poorer residents to migrate out. They refer to this as "endogenous gentrification".

Panel A of Figure 11 shows a sharp negative relationship between the initial home prices in 12 largest metros before the Covid-19 pandemic and the subsequent FHFA HPI percentage change in that Census tract. On average, tracts with lower initial home prices appreciated several times the rate as tracts with higher initial housing prices during the pandemic. Panel B of Figure 11 shows the relationship between the 2019-2021 FHFA HPI growth and the percentage of appraisals below contract in 2021. Tracts that saw larger increases in their HPI also saw a larger share of appraisals coming in below contract price.

Other important factors such as housing supply impact rates of home price appreciation in response to demand shocks. Baum-Snow and Han (2024) note that accurately quantifying housing supply elasticities at a micro-geographic level is essential for analyzing various phenomena linked to neighborhood-level variations in housing demand within cities. The authors note that shifts in housing demand driven by factors such as targeted neighborhood investments for economic development, new transportation infrastructure, changes in labor market conditions, and modifications in local amenities and public goods, all impact different neighborhoods in distinct ways. The authors note that the effects of these changes on the welfare of renters versus homeowners largely depend on neighborhood-specific housing supply elasticity estimates. The authors not that these elasticities are crucial for assessing the effectiveness of housing affordability policies, understanding the spatial variation of housing market cycles within metropolitan areas, and determining whether urban growth leads to densification or sprawl. Generally, supply responses increase with distance from central business districts due to greater availability of undeveloped land, flatter terrain, and less restrictive regulations.

Figure 12 plots the percent of appraisals that came in below contract price for a given census tract in 2021 and the housing supply elasticity estimates as provided by Baum-Snow and Han (2024) [11] for the 12 largest metros. The plot shows a 'fanning out' pattern where housing supply in tracts that are less responsive to home prices tend to see both a higher percent of appraisals coming in below contract price along with higher variation. Thus appraising in areas where housing supply is less responsive appear to play a factor.

[11] Rather than being used to evaluate policies affecting specific tracts, (Baum-Snow and Han, 2024) note that the elasticity estimates are thus probably better used in policy evaluation for a broad set of tracts, across which idiosyncratic differences in regulation can average out.

7 Conclusion

The shift toward remote work, accelerated by the COVID-19 pandemic, has profoundly reshaped urban life and labor markets. Before the pandemic, many workers were tied to expensive urban centers because of job proximity. However, with the widespread adoption of remote work, the need for employees to live near their offices has diminished. This shift has led to a significant decline in demand for commercial real estate, particularly in central business districts. As a result office occupancy rates, net population and net business establishments have fallen in these areas.

Between December 2019 and December 2021, U.S. home prices surged by an astounding 25%, marking the fastest rate of growth on record in the United States. Extensive research has documented that the growth in demand for less densely populated areas has contributed to a flattening of the bid-rent curve. While home prices began to soar during the pandemic, one insight documented in the literature is the fact that we saw a larger impact on the rent gradient relative to the home price gradient. A key area that went unexplored in the literature entails understanding how home appraisers reacted to this sudden spike in housing demand and what impact did this have on home valuations.

During the housing boom and bust of the early 2000s, appraisers played a controversial role in inflating property values, contributing to the eventual market collapse. As demand for homes surged and lending standards loosened, many appraisers faced pressure from lenders, mortgage brokers, and real estate agents to provide higher appraisals to secure larger loans. Some appraisers succumbed to this pressure, inflating home values beyond their true worth, which allowed buyers to borrow more than the property was worth

In this paper I analyses the impact of the Covid-19 induced WFH shift on the accuracy of home appraisals in the 12 largest Metropolitan Areas in the United States. To interpret the home appraisal data, I consider a WFH shock in a canonical urban model of housing in cities. I also present a simple stylized model of the property value estimation process from the perspective of a representative appraiser to conceptualize an appraisers best response to a housing demand shock when determining the value of a subject property. To empirically examine the impact of the shift to remote work on home appraisal accuracy, I analyze a dataset of appraisal records provided by the Federal Housing Finance Agency between 2013 and 2021.

I find supportive evidence that the 128% increase in home appraisal coming in below contract price in 2021 for the 12 largest metros was in part due to appraisers not fully capturing how housing demand increased and shifted geographically due to WFH. I find a significant increase in the probability of an appraisal coming in below contract price during the first two years of the Covid 19 pandemic and that these increases were mainly focused in suburban areas where housing demand increased the most. As a measure of the extensive margin, I find evidence that the contract price and appraised value difference also significantly increased during this time, mainly in suburban areas. I also find that appraised values tended to deviate further away from their contract price as the density of appraisals decreased. I find that when analyzing homes for which all the comps used were within the same census tract as the subject property, homes appraised using 7 or more comps tended to come in below contract price more often relative to homes appraised using 4 comps.

The future path of demand may depend critically on the path of remote work. The primary task of a home appraiser is to produce the best possible estimate of the market value of a subject property. Gaining better insights into the trajectory of housing demand as the WFH trend progresses should be of high priority amongst home appraisers.

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Table 1: Summary Statistics: Uniform Appraisal Dataset: Appraisal-Level Public Use File

Variable	Obs	Mean.	Std.	Min	Max
Contract Price	111,430	415,045	212,864	25,000	1,705,000
Appraised Value	265,558	479,446	284,324	25,000	1,705,000
Spread	111,430	-4,274	17,362	-750,000	670,000
CBD	265,558	.007	.088	0	1
CBS to Five Miles	265,558	.024	.154	0	1
Five to Ten Miles	265,558	.093	.290	0	1
Over Ten Miles	265,558	.874	.331	0	1
Bedrooms	265,558	2.355	.649	1	9
Bathrooms	265,558	2.579	.856	1	9
Gross Living Area	265,558	4.716	2.341	1	9
Average Comp Adjustment	265,556	-2,177	22,082	-250,000	250,000
Comps	265,558	5.291	1.067	3	7
Comps Same Tract	265,470	.643	.321	0	1
Year	265,558	2017	2.676	2013	2021
Property Condition:					
New Construction	265,558	.039	.195	0	1
Good as New	265,558	.072	.258	0	1
Well Maintained	265,558	.686	.463	0	1
Deferred Maintenance	265,558	.201	.401	0	1
Obvious Deferred Maintenance	265,558	.0003	.0189	0	1
Property Quality:					
Architect Designed Home	265,558	.0006	.026	0	1
Custom Home	265,558	.014	.119	1	
High Quality Tract Home	265,558	.372	.483	0	1
Standard Tract Home	265,558	.605	.488	0	1
Inexpensive Tract Home	265,558	.007	.084	0	1
Property Value Trends:					
Increasing	265,558	.223	.416	0	1
Stable	265,558	.769	.421	0	1
Declining	265,558	.007	.086	0	1
Demand and Supply:					
Shortage	265,558	.210	.407	0	1
Balance	265,558	.769	.421	0	1
Over Supply	265,558	.020	.140	0	1
Marketing Time:					
Less Than Three Month	265,558	.670	.470	0	1
Two to Three Month	265,558	.323	.467	0	1
Greater Than Six Months	265,558	.006	.081	0	1

Notes: Table 1 repots summary statistics for the UAD Appraisal-Level Public Use File provided by the Federal Housing Financing Agency. for the years 2013-2021. 'Property Condition' and 'Property Quality' shortened variable descriptions borrow from (Eriksen et al., 2020).

Table 2: Contract Price, Appraised Value Difference: Two Year Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	Spread 2018-19	Spread 2018-19	Spread 2018-19	Spread 2020-21	Spread 2020-21	Spread 2020-21
CBD	-1296.3	-1344.3	-976.9	-482.1	-91.28	270.3
	(1424.1)	(1402.8)	(1400.7)	(1401.9)	(1400.3)	(1428.2)
Five To Ten Miles	715.2	1127.3	1184.5	1128.4	1482.7	1508.9
	(1039.3)	(1040.1)	(1032.3)	(806.6)	(806.9)	(815.7)
Over Ten Miles	1892.5*	3206.7***	3246.1***	3062.9***	4065.7***	4019.5***
	(946.9)	(956.1)	(944.0)	(697.2)	(703.3)	(733.9)
UAD APUF Controls		✓	✓		✓	✓
ACS Controls			✓			✓
Fixed Effects		✓	✓		✓	✓
N	25486	25480	24614	30064	30053	28941
R^2	0.001	0.017	0.020	0.003	0.013	0.016

Standard errors in parentheses

$* \ p < 0.05$, $** \ p < 0.01$, $*** \ p < 0.001$

Notes: Table 2 reports two-year $SPREAD$ estimates for the 12 largest metropolitan areas in the United States. Column1 through Column 3 report estimates for the combined years 2018 and 2019 adjusting for various control variables and Column 4 through Column 6 report estimates for the combined years 2020 and 2021, likewise adjusting for various control variables. Each distance measure estimate is in reference to census tracts that are just outside the CBD yet within 5 miles of the center point of the CBD (City Hall). All standard errors are clustered at the tract level.

Table 3: Contract Price, Appraised Value Difference: One Year Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	Spread 2019	Spread 2019	Spread 2020	Spread 2020	Spread 2021	Spread 2021
CBD	735.5	593.2	-1213.9	-633.3	142.6	1074.4
	(1965.3)	(1944.1)	(1831.9)	(1847.7)	(2175.5)	(2236.6)
Five To Ten Miles	2850.0*	2888.7*	278.0	417.2	1935.0	2511.2*
	(1444.9)	(1425.2)	(1011.1)	(1024.4)	(1195.6)	(1208.1)
Over Ten Miles	2928.5*	3878.1**	1716.3*	2220.6*	4378.3***	5803.8***
	(1357.4)	(1339.6)	(838.3)	(875.7)	(1062.1)	(1112.4)
UAD APUF Controls		✓		✓		✓
ACS Controls		✓		✓		✓
Fixed Effects		✓		✓		✓
N	12953	12506	15180	14582	14884	14359
R^2	0.001	0.017	0.001	0.017	0.002	0.016

Standard errors in parentheses

$* \, p < 0.05$, $** \, p < 0.01$, $*** \, p < 0.001$

Notes: Table 3 reports one-year $SPREAD$ estimates for the 12 largest metropolitan areas in the United States. Column 1 and Column 2 report estimates for the year 2019 adjusting for various control variables. Column 3 and Column 4 report estimates for the year 2020, Column 5 and Column 6 report estimates for the year 2021, likewise adjusting for various control variables. Each distance measure estimate is in reference to census tracts that are just outside the CBD yet within 5 miles of the center point of the CBD (City Hall). All standard errors are clustered at the tract level.

Table 4: Below Contract Price Probability, Marginal Effects: Two Year Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	BCP 2018-19	BCP 2018-19	BCP 2018-19	BCP 2020-21	BCP 2020-21	BCP 2020-21
CBD	-0.051*	-0.054*	-0.050*	-0.027	-0.026	-0.015
	(0.024)	(0.023)	(0.024)	(0.025)	(0.025)	(0.026)
Five to Ten Miles	-0.002	0.003	0.005	0.029	0.035*	0.040**
	(0.010)	(0.010)	(0.010)	(0.016)	(0.015)	(0.015)
Over Ten Miles	0.004	0.016	0.021*	0.063***	0.073***	0.081***
	(0.009)	(0.009)	(0.009)	(0.014)	(0.014)	(0.014)
UAD APUF Controls		✓	✓		✓	✓
ACS Controls			✓			✓
Fixed Effects		✓	✓		✓	✓
N	25486	25480	24614	30,064	30053	28941

Standard errors in parentheses

$* \; p < 0.05$, $** \; p < 0.01$, $*** \; p < 0.001$

Notes: Table 4 reports the two-year probit estimates of the marginal effect for the 12 largest metropolitan areas in the United States. Column1 through Column 3 report estimates for the combined years 2018 and 2019 adjusting for various control variables and Column 4 through Column 6 report estimates for the combined years 2020 and 2021, likewise adjusting for various control variables. Each distance measure estimate is in reference to census tracts that are just outside the CBD yet within 5 miles of the center point of the CBD (City Hall). All standard errors are clustered at the tract level.

Table 5: Below Contract Price Probability, Marginal Effects: One Year Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	BCP -2019	BCP -2019	BCP -2020	BCP -2020	BCP-2021	BCP -2021
CBD	-0.016	-0.017*	-0.054	-0.041	0.008	-0.017
	(0024)	(0.024)	(0.32)	(0.033)	(0.044)	(0.044)
Five to Ten Miles	0.021	0.026	0.011	0.019	0.051*	0.062*
	(0.014)	(0.014)	(0.017)	(0.016)	(0.025)	(0.025)
Over Ten Miles	0.020	0.033*	0.018	0.031	0.117***	0.138***
	(0.013)	(0.013)	(0.015)	(0.016)	(0.023)	(0.023)
UAD APUF Controls		✓		✓		✓
ACS Controls		✓		✓		✓
Fixed Effects		✓		✓		✓
N	12953	12506	15180	14582	14884	14359

Standard errors in parentheses

$* \, p < 0.05$, $** \, p < 0.01$, $*** \, p < 0.001$

Notes: Table 5 reports one-year probit estimates of the marginal effect for the 12 largest metropolitan areas in the United States. Column 1 and Column 2 report estimates for the year 2019 adjusting for various control variables. Column 3 and Column 4 report estimates for the year 2020, Column 5 and Column 6 report estimates for the year 2021, likewise adjusting for various control variables. Each distance measure estimate is in reference to census tracts that are just outside the CBD yet within 5 miles of the center point of the CBD (City Hall). All standard errors are clustered at the tract level.

Figure 1: Percent of Appraisals Below Contract Price

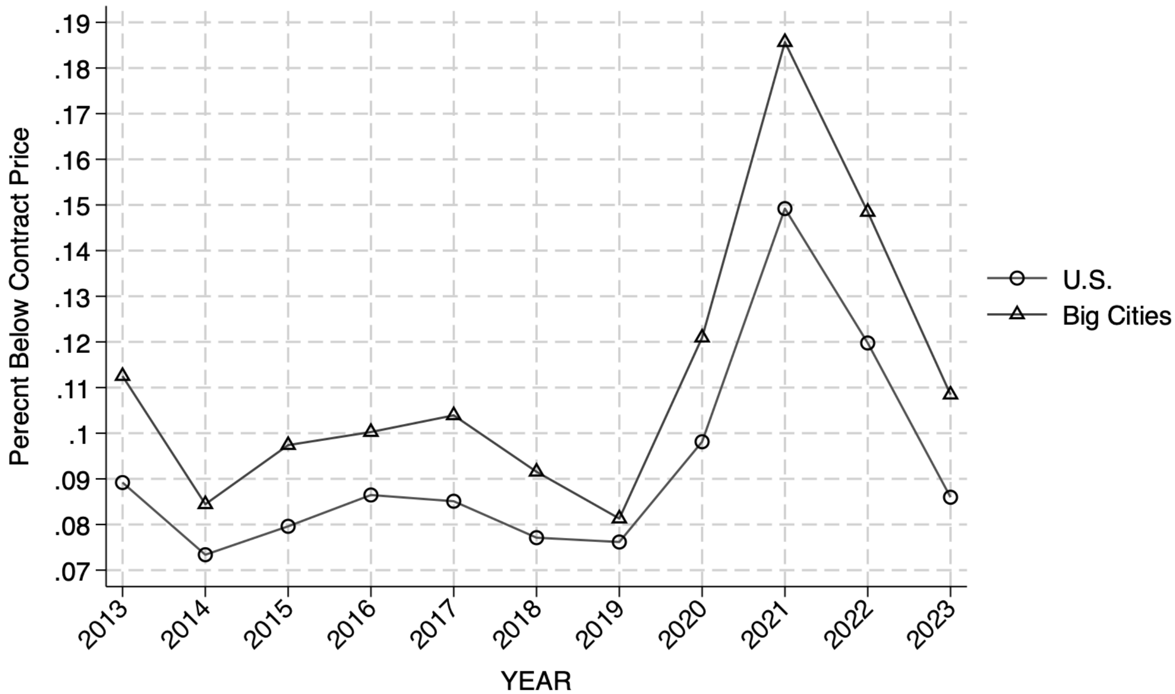
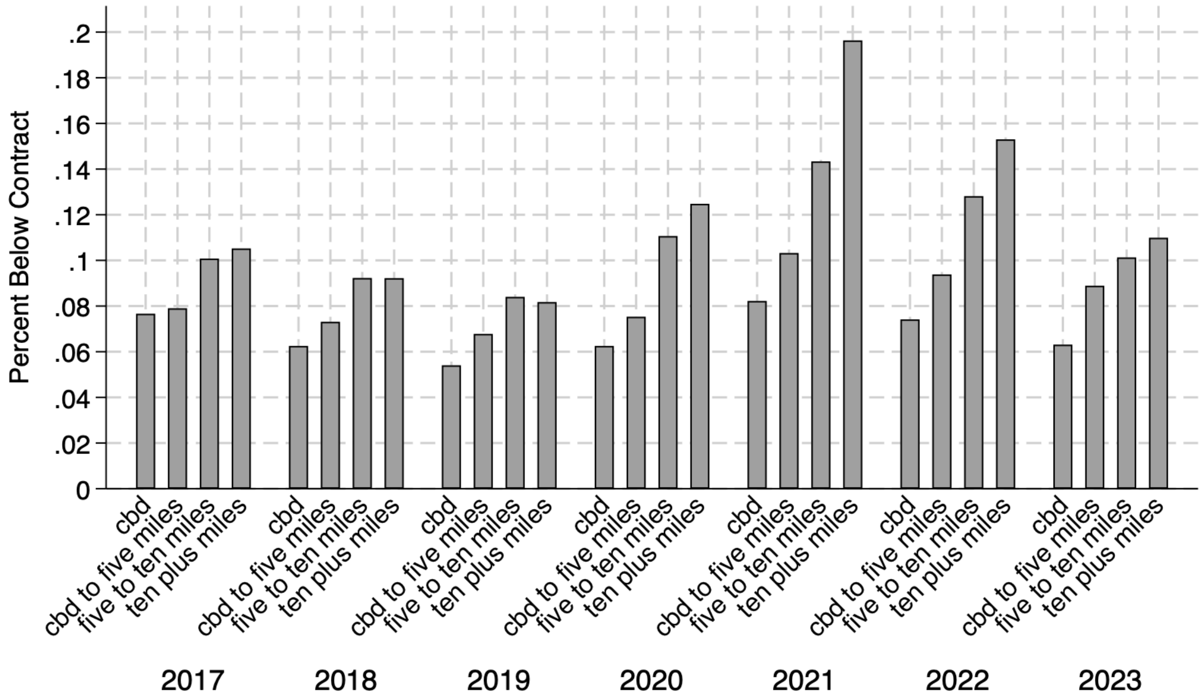


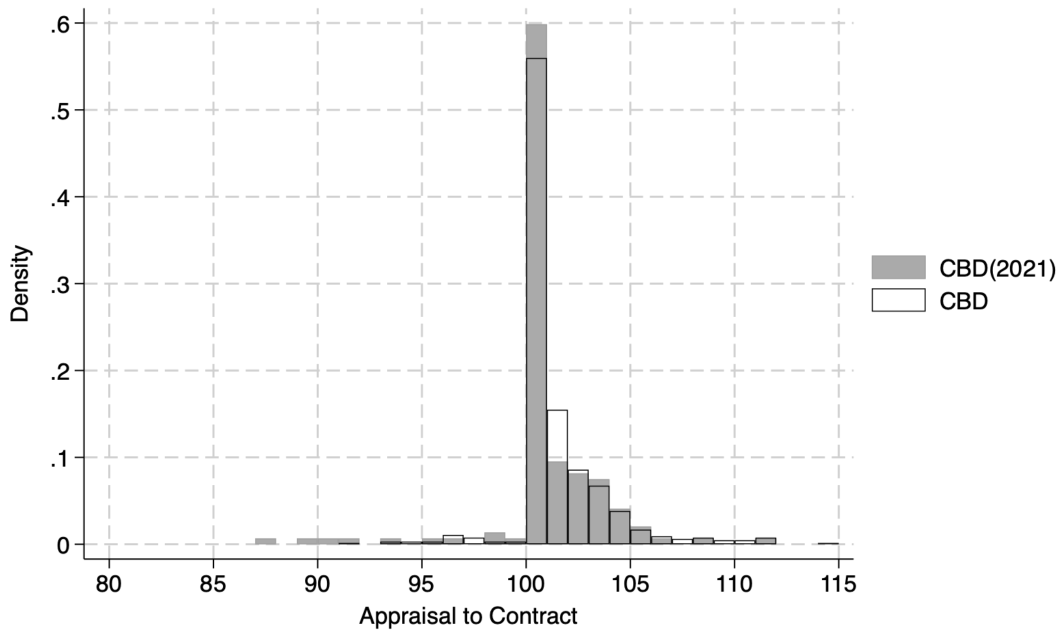
Figure 1 plots the percent of appraisals that appraised below contract price for the years 2013-2023. The "Big Cities" plot consists of the largest 12 Metropolitan Areas in the United States, namely: Atlanta, Boston, Chicago, Dallas, Houston, Los Angeles, Miami, New York City, Phoenix, Philadelphia, SanFrancisco, Washington DC. The U.S. plot includes the 12 largest metros.

Figure 2: Percent Below Contract: By Distance

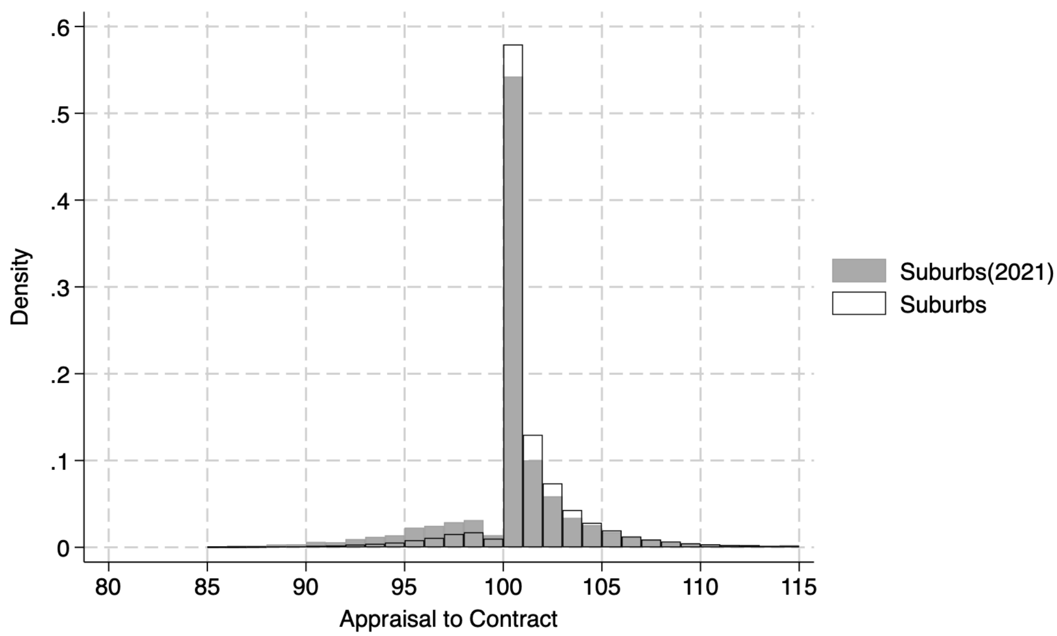


Notes: Figure 2 plots the percent of appraisals that appraised below contract price for the years 2013-2023 by distance to the Central Business District for the largest 12 Metropolitan Areas in the United States, namely: Atlanta, Boston, Chicago, Dallas, Houston, Los Angeles, Miami, New York City, Phoenix, Philadelphia, SanFrancisco, Washington DC. The CBD is defined census tracts that are within a 1.75 mile radius of City Hall for each respective metropolitan area. Census tracts that are "ten plus miles" from the CBD are all within the metropolitan area of the CBD.

Figure 3: 2021 Percent Below Contract: Distribution



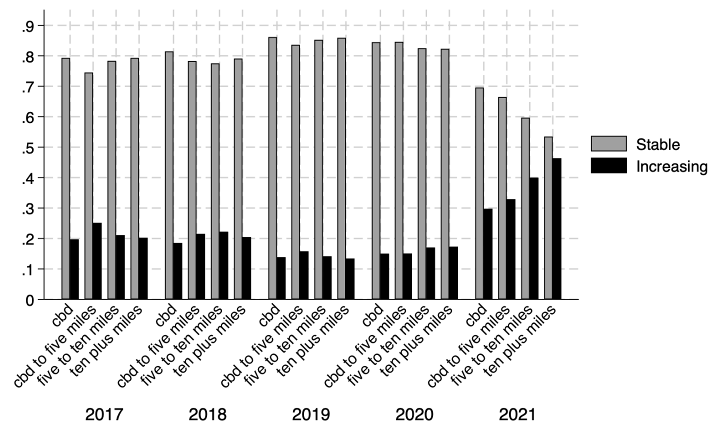
(A) Central Business District



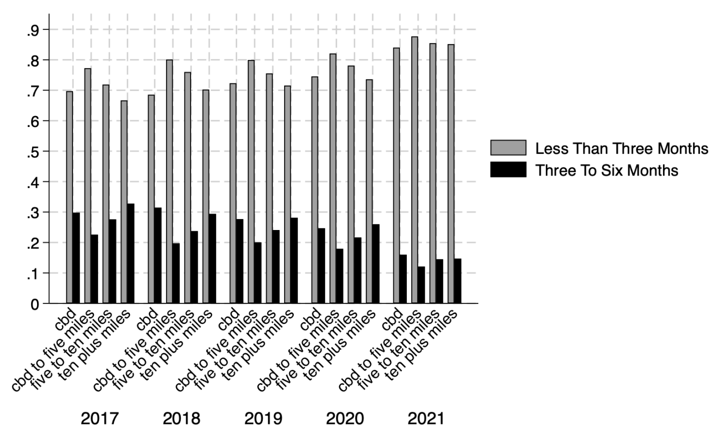
(B) Suburbs

Notes: Figure 3 plot the distribution of the “home appraisal to contract price ratio” for appraised homes within the CBD and homes 10 miles or more from the CBD in 2021 respectively. Panel A plots the distribution for the CBD and Panel B plots the distribution for homes 10 miles or more from the CBD. For each panel, the dark shade distributions reports data for the year 2021 and the white distribution plots the 2017-2019 average. Each distribution uses data for the largest 12 Metropolitan Areas in the United States.

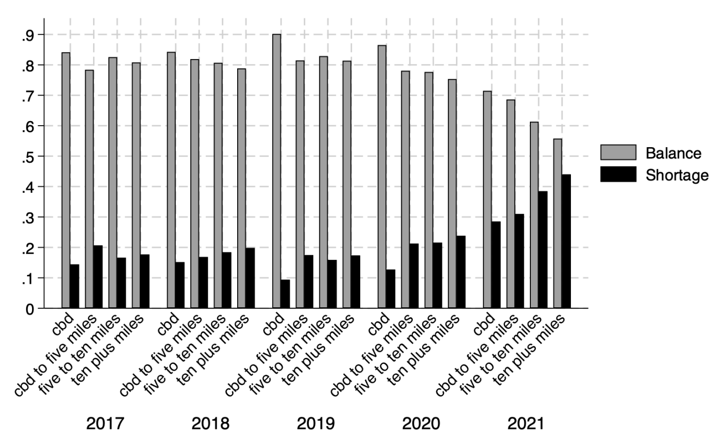
Figure 4: Housing Market Temperature



(A) Local Property Value Trends



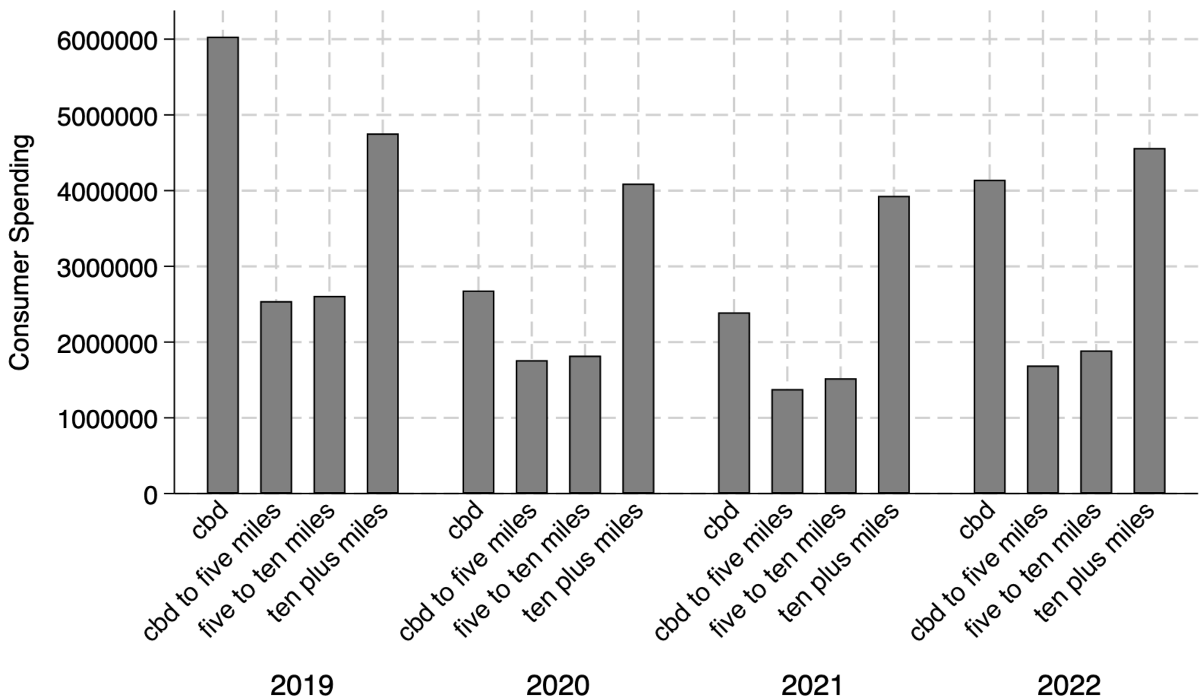
(B) Marketing Time



(C) Demand vs. Supply

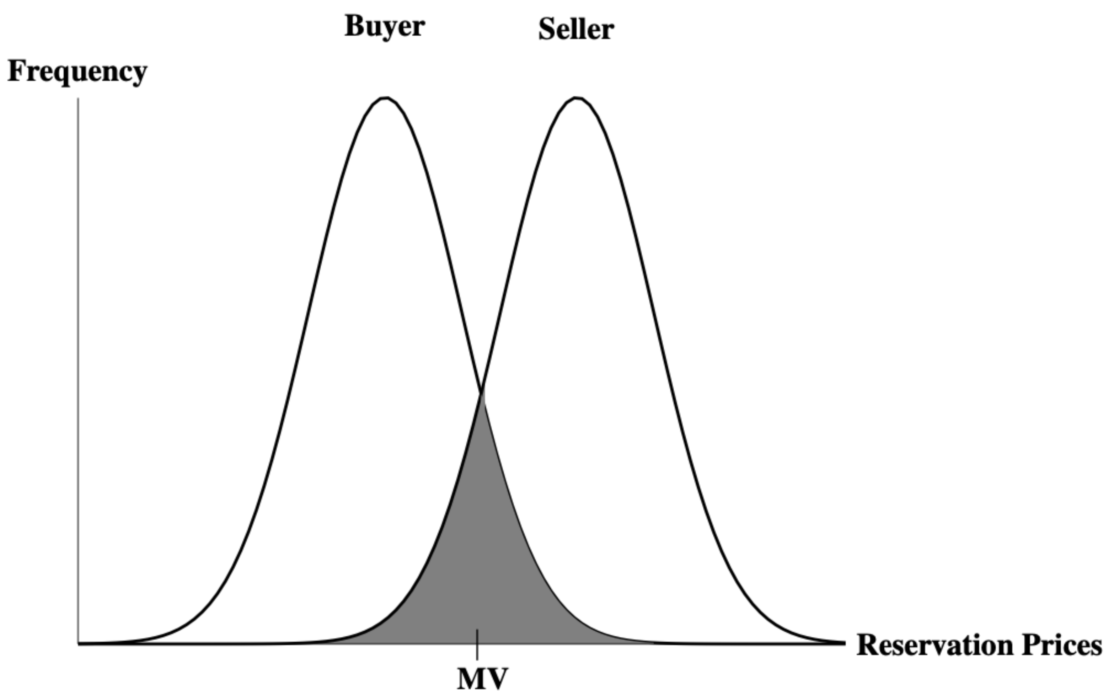
Notes: Figure 4 plots appraiser reported market trends in the local area of the subject property based on: the typical length of time a property would stay on the market before being sold in the neighborhood, the local property value trends of one-unit property values in the subject's neighborhood and trends concerning housing demand versus housing supply in the neighborhood. Each Panel uses data for the largest 12 Metropolitan Areas in the United States.

Figure 5: SafeGraph: Consumer Spending



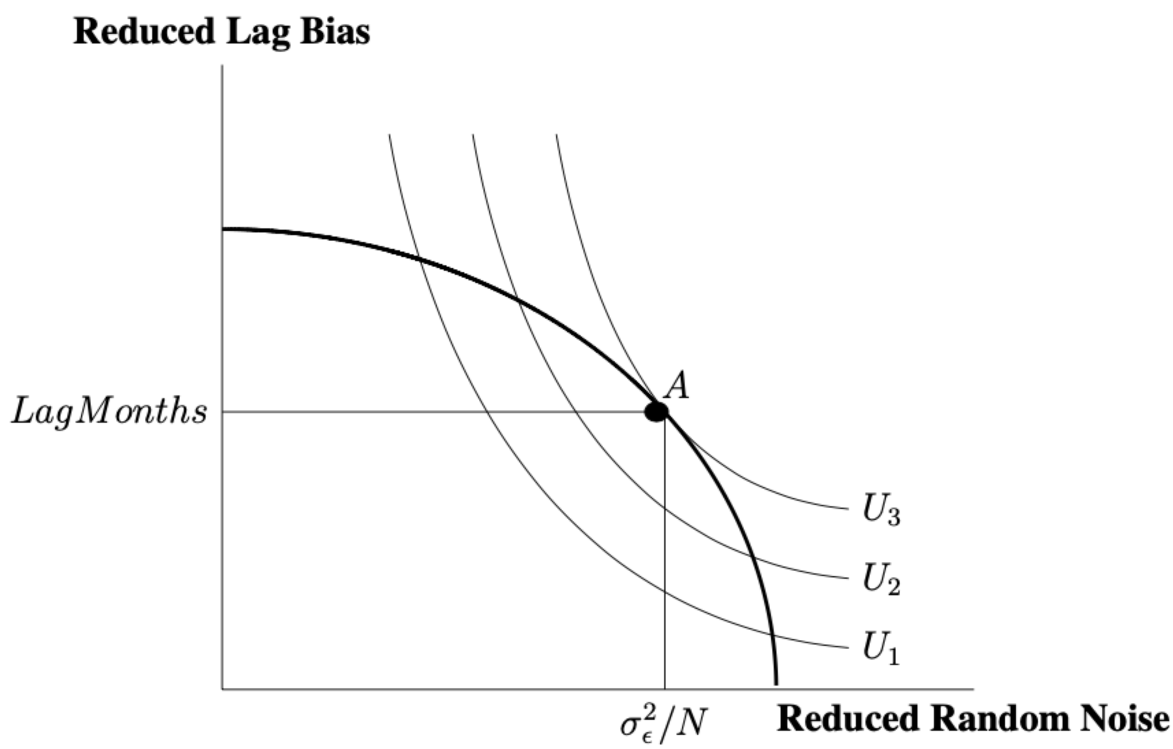
Notes: Figure 5 shows trends in consumer spending as measured by SafeGraph's mobility data. The dataset aggregates anonymized debit and credit card transaction data for individual establishments in the United States. The Figure uses data for the largest 12 Metropolitan Areas in the United States.

Figure 6: Buyer and Seller Populations, Reservation Price Frequency Distributions



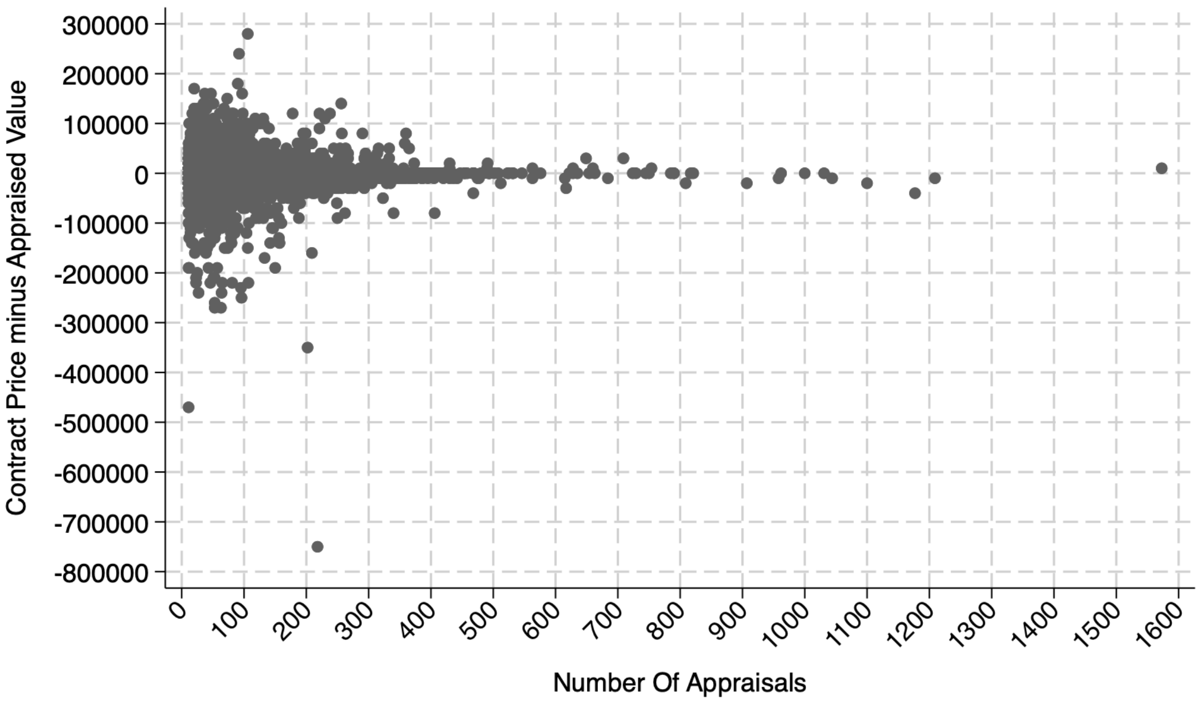
Notes: Figure 6 shows the overlapping distribution of potential buyers and sellers reservation prices within a population of properties at a given point in time. The figure indicates that transactions in this market may occur in the overlapping gray shaded region where some buyers will have reservation prices at least as high as the reservation prices of some sellers.

Figure 7: Noise vs. Lag Trade-off Frontier



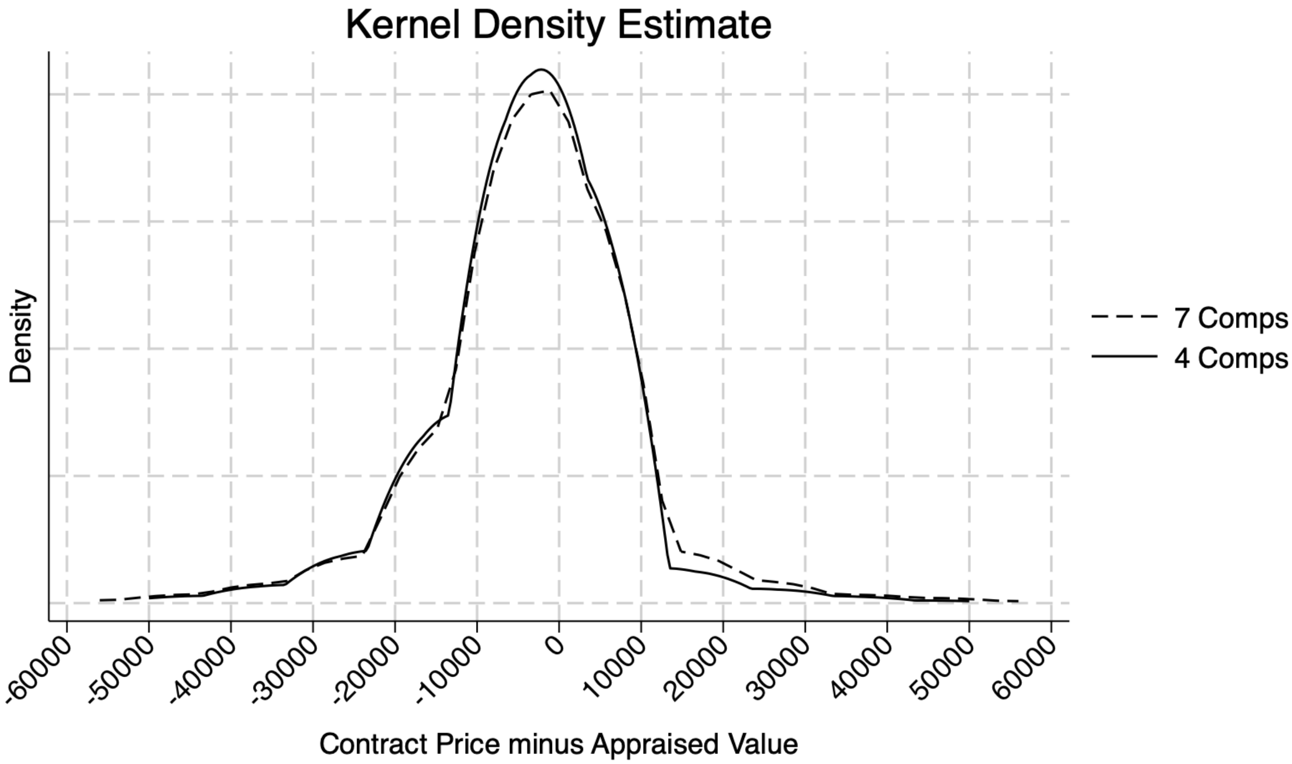
Notes: Figure 7 shows the Noise vs. Lag Trade-off Frontier. The two axes represent the two types of error, arranged so that the farther out from the origin, the less the error. The horizontal axes represents greater precision in the value estimate, that is, less purely random error. Points farther to the right of the axis have less noise. The vertical axis represents less temporal lag bias. The thick solid concave curve represents the frontier. Points outside of the frontier are not feasible.

Figure 8: Contract Price and Appraised Value Difference, 2021



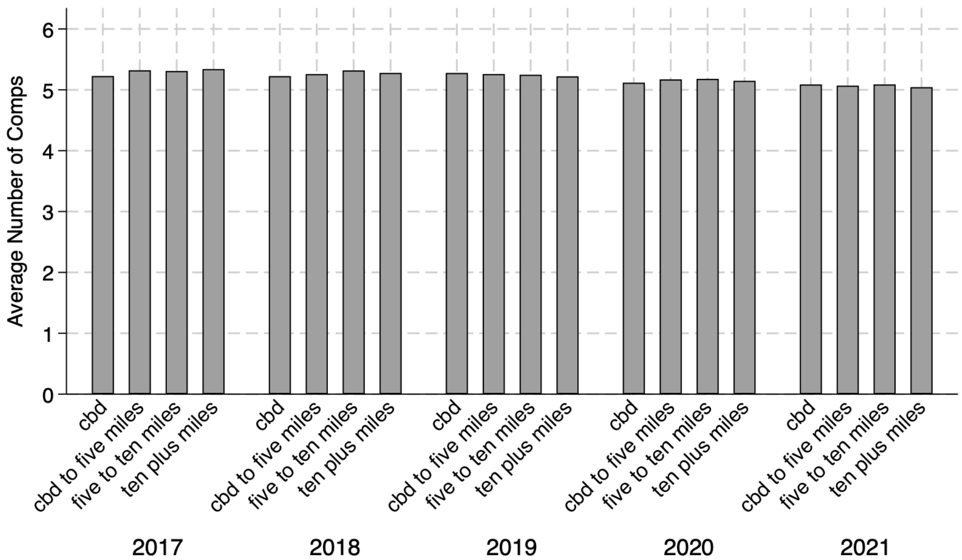
Notes: Figure 8 plots the 2021 average contract price and appropriated value difference for census tracts as a function of the total number of appraisals in that census tract. The price difference is measured using the UAD APUF data set while the total number of appraisals is measured using the UAD aggregated statistics data set.

Figure 9: Percent Below Contract: Seven vs. Four Comps, 2021

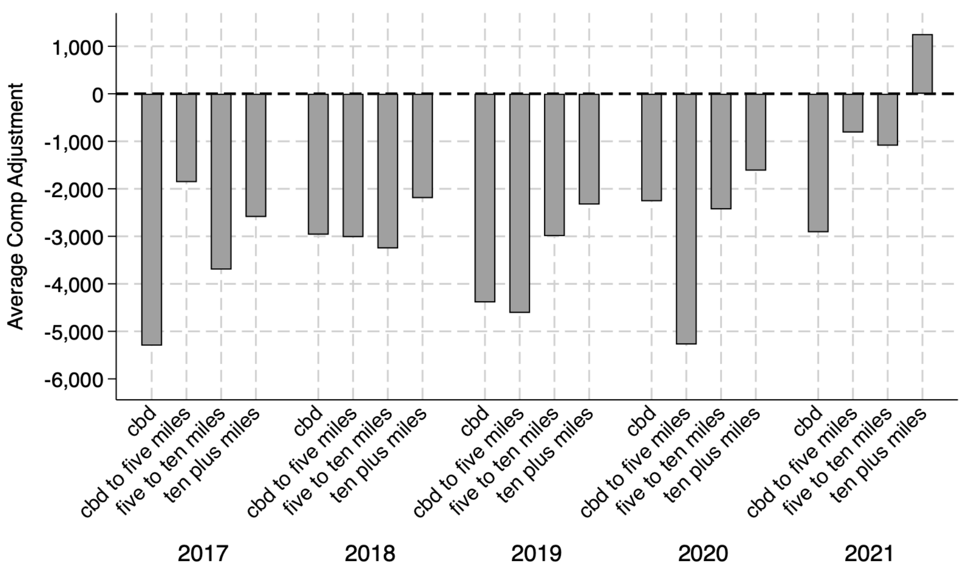


Notes: Figure 9 shows the density plots of the contract price and appraised value difference for the year 2021. The solid distribution plots the contract and appraised value difference for the subject properties that use 4 comps to conduct the appraisal and the dashed distribution plots the difference where "7 or more" comps were used. To adjust for potential neighborhood factors, Figure 9 only plots the difference for subject properties where all the comps used where within the same census tract as the subject property. Figure 9 also adjusts for the sample size differences that may effect the shape of the distribution. To adjust for this difference, I randomly selected 36% of subject properties that used 4 comps sample to equate it with the 7 or more sample. Roughly 2,700 appraisals are used for each density plot. Again, note that the APUF dataset is a five percent representative sample.

Figure 10: Comparable Properties



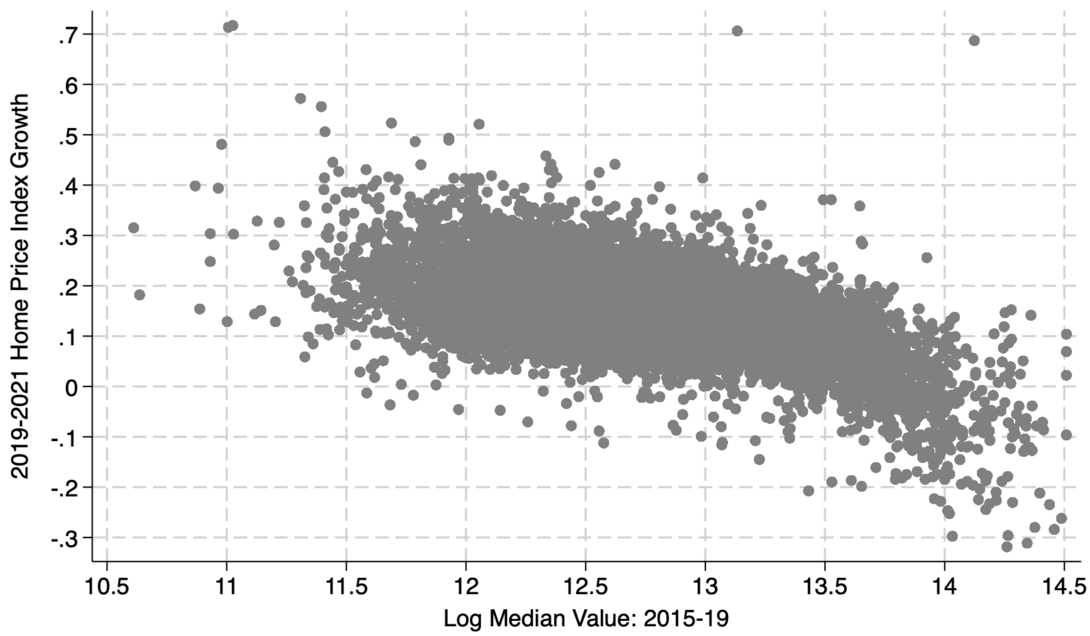
(A) Average Number of Comps Used Per Appraisal



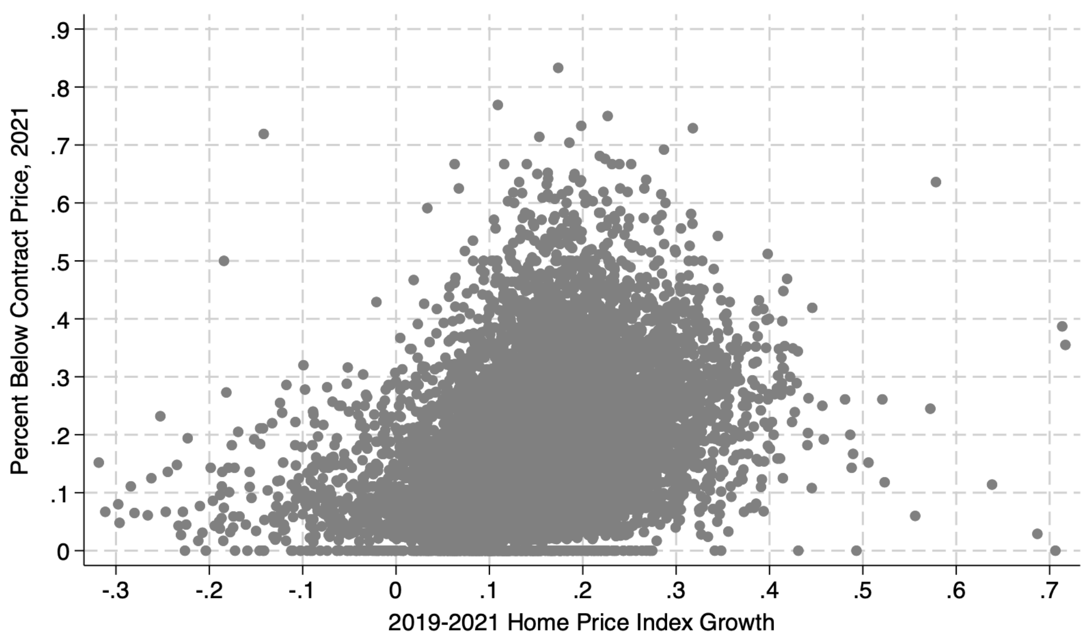
(B) Average Comp Adjustment For Appraised Property

Notes: Panel A of Figure 10 plots the average number of comps used over time by distance to the CBD. Panel B of Figure 10 plots the average dollar value of comps adjustments made by apprisers over time by distance to the CBD.

Figure 11: Appraisals Below Contract by Home Price Appreciation



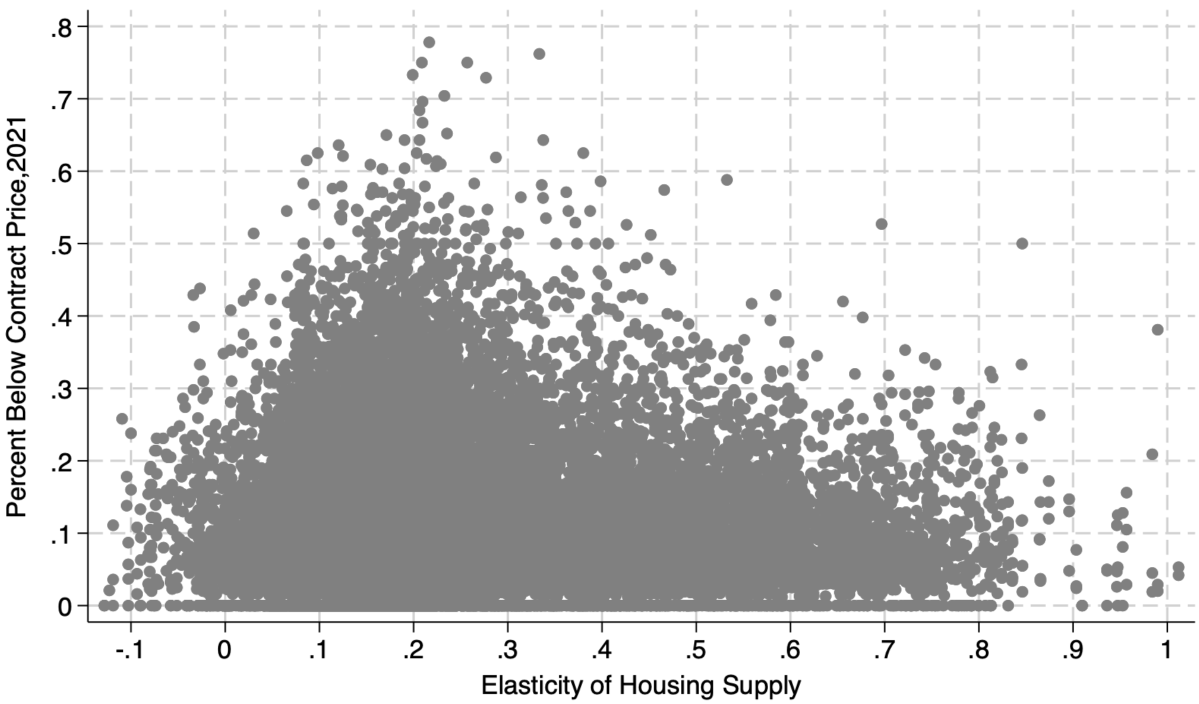
(A) Home Price Appreciation



(B) Percent Below Contract Price

Notes: Panel A of Figure 11 plots the initial 2015-2019 median home price in a Census tract before the Covid-19 pandemic versus the subsequent 2019-2021 FHFA HPI growth. Panel B plots the relationship between the 2019-2021 FHFA HPI growth and the percentage of appraisals below contract in 2021

Figure 12: Appraisals Below Contract by Housing Supply Elasticity



Notes: Figure 12 plots the percent of appraisals below contract price for a given census tract in 2021 and the housing supply elasticity estimates provided by (Baum-Snow and Han, 2024)