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FROM NOVELTY TO NORM:
UNCOVERING THE DRIVERS OF VIRTUAL TOUR EFFECTIVENESS IN REAL ESTATE SALES

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ABSTRACT

This study examines the effectiveness of virtual tours and digital marketing strategies in enhancing real estate sales using a unique dataset combining MLS data, government-assessed property values, and agents' marketing activities. While virtual tours are often perceived as a powerful tool to boost sales, their impact is context-dependent. Using classical econometric models and causal machine learning techniques, we find that virtual tours increase property sale prices by an average of 1%. However, the effect has declined over time, particularly post-COVID, indicating a shift from being a novel feature to a standard practice. Further analysis using causal random forests reveals significant heterogeneity in their effectiveness across property attributes, market conditions, and agent characteristics. Virtual tours are less impactful for highly differentiated properties but more beneficial in competitive markets and for less experienced agents who lack familiarity with the local market. These results suggest that real estate agents may benefit from considering property features, market dynamics, and their own experience when deciding how to use virtual tours. Our findings offer valuable insights for practitioners looking to optimize digital marketing strategies and enhance sales performance.

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I. Introduction

In markets characterized by substantial heterogeneity and elevated search costs, inefficiencies often arise due to information asymmetry and uncertainty. This challenge is especially relevant in real estate, where the information imbalance between buyers and sellers can complicate property transactions, and buyers have to literally live with their purchases for years (Garmaise & Moskowitz, 2004; Kurlat & Stroebel, 2014). In response, real estate agents are investing heavily in marketing, dedicating around 10% of gross commission income to advertising—considerably more than other sectors (Hessinger, 2018). With global real estate advertising expenses projected to rise from approximately $30.4 billion in 2019 to $41.4 billion by 2024 (Wood, 2019), understanding the efficacy of various communication tools remains a priority for both researchers and practitioners. This study examines the impacts of an innovative modern marketing instrument, virtual tours, on sales performance in the real estate market by exploring the mechanisms underlying these effects.

The adoption of online platforms and tools like virtual tours has greatly improved property information accessibility. Platforms such as Zillow now allow agents to present properties through virtual tours, offering buyers a more immersive experience. Recent surveys show that consumers value virtual tours highly, particularly for in-depth property exploration (Ratiu, 2020). This digital shift has intensified post-COVID-19, transforming marketing approaches in real estate (Hoban, 2021), and properties with virtual tours on Zillow in early 2020 attracted 50% more user 'saves' and sold about 10% quicker than those without (Olick, 2020).

Virtual tours facilitate information gathering and buyer matching but come with trade-offs. Costs range from $100 to over $1,000 (Snyder & Main, 2022), and the two-stage search process in real estate complicates the effectiveness of added information disclosure. On platforms like

Airbnb, high-quality images and additional information have been shown to increase booking rates by boosting trust and reducing uncertainty. For example, Zhang et al. (2022) found that verified images raised occupancy by nearly 9%. In addition, He et al. (2023) and Li et al. (2023) demonstrated that strategic photo features and layouts can increase demand, underscoring the role of visuals in consumer decisions on peer-to-peer platforms. In contrast, real estate buyers typically engage in a two-stage process. Online listings generate interests, but the final decision follows an in-person visit. This distinction highlights virtual tours as tools to enhance initial engagement rather than close sales. Even during COVID-19, 63.6% of consumers still required physical visits before purchase (Ratiu, 2020).

Research on the effectiveness of virtual tours in real estate shows mixed results: some studies link virtual tours to higher sales prices and shorter durations (Allen et al., 2015; Andersen et al., 2022), while others find they can prolong time on the market (Benefield et al., 2019; Yu et al., 2021). These differences may stem from endogeneity issues, as virtual tour adoption can correlate with unobserved property features or conditions. Recent studies emphasize the value of online information in supporting offline transactions (Jiang et al., 2024) or suggest that virtual tours have conditional impacts, with higher effectiveness in mid-priced segments (Hsiao et al., 2024) and marginal effects depending on market specifics (Zhang & Troncoso, 2023).

Our study advances the literature by using a rich dataset of over 10 years, covering 197,345 transactions in Vancouver, Canada. This long-term perspective allows us to track how virtual tour effectiveness has shifted as these tools have evolved from novel features to standard practices, particularly post-COVID-19. This extended timeframe enables a unique assessment of the sustained value of virtual tours where such tools have become more normalized post-COVID-19.

We apply a rigorous framework to explore causal relationships and variation in virtual tour impacts on real estate sales. Using advanced econometric and machine learning techniques such as 2SLS, 2sCOPE, and causal random forests, we clarify the mechanisms by which virtual tours influence sales. Our research addresses three questions: 1) How do virtual tours affect real estate sales? 2) Is there heterogeneity in their effects? 3) What mechanisms explain these effects?

Our analysis reveals that virtual tours significantly increase sold prices, indicating market preference for enhanced information. Employing techniques such as 2SLS, 2sCOPE, and causal random forests allows us to address endogeneity and capture causal effects. We find that virtual tours are most effective in less differentiated markets where property standardization is high. In contrast, in highly differentiated markets, their benefits are less pronounced. Interestingly, while virtual tours have become popular post-COVID-19, their effectiveness appears to have decreased over time. Our results suggest that signaling, search facilitation, and cognitive salience drive virtual tour effectiveness, offering a comprehensive view of their impact on sales.

II. Literature Review

Marketing research in the real estate context has gained substantial attention in recent years, reflecting the field's growing relevance and the unique challenges it presents in information asymmetry, consumer behavior, and market dynamics. Studies have explored various aspects of real estate marketing, including pricing mechanisms, the role of intermediaries, and the impact of digital platforms. For example, Wang (2024) examined the effects of for-sale-by-owner (FSBO) platforms on intermediation pricing, illustrating how digital disruption is transforming traditional real estate practices and affecting market outcomes. Barron et al. (2021) analyzed the impact of short-term rental platforms like Airbnb on residential house prices, highlighting the broader influence of digital innovations on real estate markets. Similarly, Bekkerman et al. (2022) investigated the effect of short-term rentals on residential real estate investment, showing how platforms like Airbnb can incentivize investment by altering housing demand and property value expectations. These studies underscore the importance of understanding digital tools and intermediaries in real estate marketing, providing a foundation for examining the role of marketing platforms and innovations in buyer engagement and decision-making in the real estate context.

Building on this stream of research, our study examines the underexplored impact of virtual tours on sales performance in real estate. To the best of our knowledge, this study is the first to propose a synthesized theoretical framework incorporating quality signaling, consumer search, and salience to explain the impact of voluntary information disclosure, specifically virtual tours, on the real estate market.

Information Disclosure and Signaling Effect

The real estate market is characterized by significant information asymmetry, with buyers often lacking full visibility into property quality (Garmaise & Moskowitz, 2004; Kurlat & Stroebel, 2014). Virtual tours serve as a salient form of voluntary disclosure, allowing sellers to reduce this asymmetry. Theoretical studies, such as those by Grossman (1981) and Milgrom (1981), illustrate the unraveling effect, where higher-quality sellers disclose more information to differentiate themselves, leading to better outcomes. Milgrom & Weber (1982) extended this with the linkage principle, showing that more disclosure can lead to higher transaction prices. Empirical studies highlight similar effects. Tucker and Zhang (2010) showed that disclosing selective network information in a two-sided market, such as user numbers on one side, boosted engagement by allowing users to infer network value—a mechanism similar to how buyers may view virtual tours as signals of property quality. Tucker et al. (2013) further found that requiring true days-on-market disclosure in real estate led buyers to make more informed judgments, which prompted sellers to adjust pricing strategies. These findings underscore how strategic information disclosure can shape buyer perceptions and influence market behaviors.

In real estate specifically, voluntary information disclosures—like additional photos (Bian et al., 2023) and school information (Carrillo et al., 2013)—are associated with favorable sales outcomes. Virtual tours, as noted by Allen et al. (2015) and Benefield et al. (2019), enhance transparency and attract buyer interests. Our study builds on these insights, proposing that virtual tours act as a quality signal, positively correlating with increased sales prices.

Consumer Search for Differentiated Products

Information disclosure can benefit sellers by engaging consumers in costly searches and improving the quality of matches (Gardete & Guo, 2021; Mayzlin & Shin, 2011). For highly differentiated products with complex attributes, consumer search is essential to achieving a quality match (Mayzlin & Shin, 2011). In the real estate market, search and match processes are crucial and have been extensively studied in the contexts of pricing (Knight, 2002), brokerage (Li & Yavas, 2015), and sales (Carrillo, 2012). Real estate's unique two-stage search involves an online phase followed by in-person visits, where attributes challenging to capture online can be fully assessed, reinforcing the role of in-person evaluation (Carrillo, 2012). Research further shows that platform choice, such as listing on MLS versus FSBO, impacts search efficiency, with MLS listings generally leading to faster sales (Hendel et al., 2007), underscoring the importance of visibility in reducing search time. In highly differentiated markets, quality differentiation can also reduce consumer search costs by providing clearer signals. Wang et al. (2024) show that Airbnb's Plus program, which tags premium listings, improves matching by minimizing discovery and evaluation costs, especially in crowded markets.

For properties with highly differentiated attributes, selective information disclosure can encourage in-person visits by leveraging curiosity and exclusivity. Less voluntary disclosure, such as fewer photos, can incentivize in-person viewings and potentially increase arrival rates (Bian et al., 2023; Lewis, 2011; Tadelis & Zettelmeyer, 2015). Prior studies have used indirect measures of differentiation—such as price (Bian et al., 2023), product age (Lewis, 2011), and quality segments (Tadelis & Zettelmeyer, 2015)—to examine the effects of disclosure. For instance, Bian et al. (2023) used Virginia MLS data to show that for highly differentiated properties, increased photo disclosure negatively impacted sales prices and time on market. Our study diverges by using a more refined measure of property differentiation, the "matched property quantity," which provides a direct assessment rather than relying on proxies.

Cognitive Salience

Virtual tours, an innovative technology, can potentially influence property sales outcomes through the salience effect. Miller & Berry (1998) defined brand salience in advertising as consumers' top-of-mind product awareness. In other words, salience refers to the degree to which a product stands out in consumers' awareness and memory. Salient information, such as virtual tours, provides additional experiences for consumers and can increase their awareness and memory of the related product, leading to a higher level of cognitive salience (Hyun et al., 2009). The positive influence of heightened salience and increased attention on consumers' product choices is well documented (Busse et al., 2013; Zhang, 2006; Zhang et al., 2009).

Most prior empirical studies on voluntary information disclosure have overlooked this potential cognitive mechanism. The research by Tadelis & Zettelmeyer (2015) is an exception, as they indirectly tested the salience effect as an alternative explanation for providing extra text reports in automobile trading. Our study provides more direct empirical evidence of the underestimated salience effect by utilizing the sudden variation in the salient level of virtual tours in our dataset caused by the external Covid-19 shock.

The importance of this factor in research cannot be overstated, especially as more people adopt innovative technologies such as virtual tours. Earlier studies have shown the significant impact of virtual tours on sales performance, but these findings may have been influenced by the context and timing when virtual tours were less common and thus more salient. As adoption rates increase, the salience of virtual tours may diminish, potentially reducing their initial impact. It is crucial to investigate how the salience effect contributes to the effectiveness of virtual tours and how this may change as the technology becomes more widespread. Understanding this trend helps us foresee future market dynamics and leverage innovations in marketing strategies to maintain their effectiveness over time.

In sum, our study differs from previous studies in several important ways. First, we consider the deviation of the sales prices to assess values of properties (released by the government every year) as our outcome measure to better proxy for performance. We further utilize multiple identification methods, including 2SLS, 2SCOPE, and causal random forest, to better mitigate endogeneity. Second, we provide micro-foundations to generalize our empirical findings on a compound effects of search theory, signaling, and salience effect. Third, with our unique dataset covering various market and property varieties, we provide a more rigorous examination of the proposed theoretical explanations. More generally, our results provide valuable insights for voluntary information disclosure in similar contexts with information asymmetry and heterogeneity, such as online used goods and art product auctions.

III. Data and Model-Free Evidence

Data Overview

We explore the impact of offering virtual tours on sales performance using an integrated dataset from the Multiple Listing Services (MLS) data in the Greater Vancouver region of British Columbia (BC, Canada) and BC property assessed values. The dataset includes 197,345 individual attached home[1] transaction data from January 2011 to August 2021. To keep relative location homogeneity, we only focus on the City of Vancouver area. Outliers are identified and removed by excluding presale properties and listings with sold price per square foot or assessed value higher than the 99.99% percentile.

The dataset covers four streams of information: property features, transactional information, agent information, and assessed values. The MLS serves as the source for the agents to report detailed fundamental property features, such as listing price, built year, address, etc. In addition, agents could offer additional media or text descriptions of the property via MLS, including virtual tours, pictures, and public remarks. Online real estate listing platforms enable potential buyers to access the MLS data, including a convenient way to display the offered virtual tours. Figure 1 shows how these property features are published on a typical online listing platform. In addition to property features, our dataset includes transactional information for each property, such as list/sold dates and prices. The MLS also provides identification numbers, years of experiences, and offices for both the seller's and buyer's agents. Furthermore, we merge the assessed values for each property on the sold year. The assessed value for each sold property is estimated independently by the BC government and updated annually[2]. This information provides

[1] Attached properties include apartment/condo, townhouse, and 1/2duplex.
[2]For more details on the governmental assessment process, please see the BC official website: https://www2.gov.bc.ca/gov/content/taxes/property-taxes/annual-property-tax/property-assessment

us with a more accurate and annually-adjusted third-party assessed property value, contributing to a more robust measure of transaction outcome.

The West Coast has been marveled as a well-coveted housing market and our database is uniquely rich in capturing the census of listing properties with a broad set of characteristics. This enables systematic analyses and understanding of the real-estate market that drives 20% of the provincial GDP (Statista, 2022)[3].

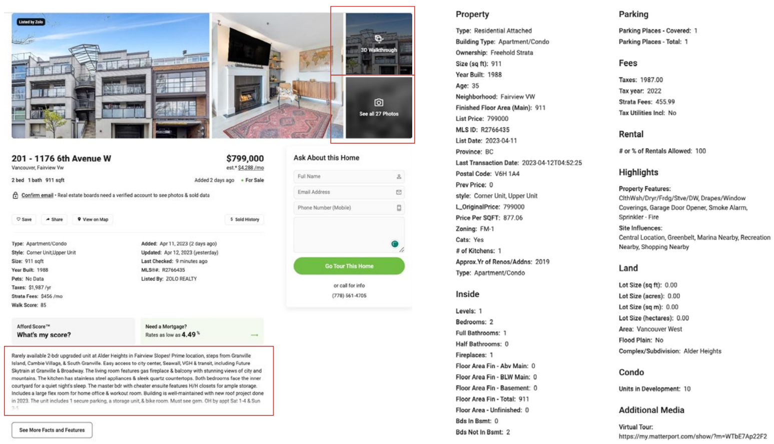


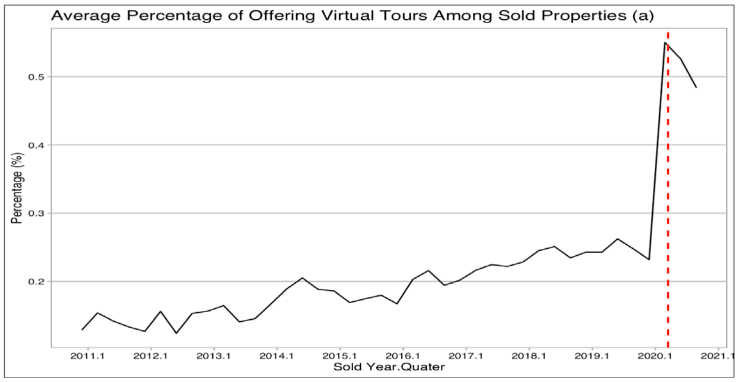
Figure 1. MLS Property Features Published on Typical Online Listing Platform

Summary Statistics and Model-Free Evidence

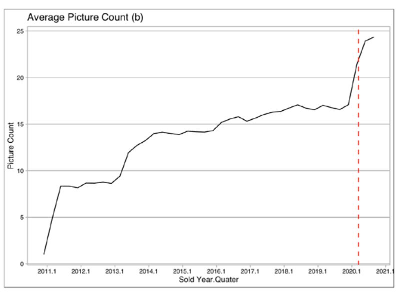
Figure 2 reports the monthly time trend of the average virtual tour offering rate, picture count, and the length of public remarks over all sold listings during the month. As is shown, there is a generally increasing trend for all three types of additional information disclosure. However, regarding the external shock of Covid-19, we only observe a remarkable spike in the average virtual tour offering rate. Prior to the pandemic, the average virtual tour offering rate was about 25%, whereas the average offering rate doubled to over 50% and stayed at an average level of about 47% after the first quarter of the pandemic. In contrast, there is merely a mild increase in the

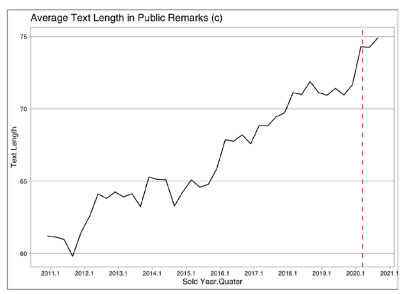
[3] https://www.statista.com/statistics/608359/gdp-distribution-of-british-columbia-canada-by-industry/ Accessed April 30, 2024.

average number of pictures and no apparent fluctuation in the length of public remarks. The notable spike in the virtual tour offering ratio contributes to uncovering the causal effect of providing virtual tours and the underlying mechanism.



(a)





(b) (c)

Figure 2. Time Trend of Average Virtual Tours Offering Percentage (a), Picture Counts (b), and Length of Public Remarks (c)
Notes: The red dash line marks the 2nd Quarter of 2020, which is the first quarter after the Covid-19 pandemic hit Vancouver.

Sales performance. We utilize the deviation of sold price from assessed value (*AssessDev*) to measure sales performance. For each sold property i, $SoldDev_i$ is defined as:

$$Assess\ Dev_i = \frac{Sold\ Price_i - Assessed\ Value_i}{Assessed\ Value_i}$$

This measure evaluates the premium the seller obtains compared to the objective benchmark value. A higher *AssessDev* indicates a higher price premium and deviation from the independently assessed property value. By investigating the relative price deviation instead of the absolute price amount[4], we could tease apart the effect of most unobserved property features, e.g., the block and building condition, since these features will simultaneously affect the absolute sold price and the assessed value. In addition, we could also exclude the potential impact of general fluctuations on sold price and buyers' location preference as the assessed value is estimated annually based on the updated transaction prices of similarly conditioned and located properties. Alternative measures such as list price, sold price, sold price per square foot, and days on the market are also included in our dataset.

Property features. Property attributes, such as the renovation condition, surrounding views, and whether the property is a luxury one, may affect both the sold price premium and the virtual tour offering. We extract these property attributes (*Renovation, View,* and *Luxury*) from public remarks using text analysis. *Renovation* captures whether the property has been renovated recently. *View* indicates whether the listing is surrounded by any water or ocean views. *Luxury* identifies whether the property is highlighted as luxury or opulent. We also evaluate the property differentiation level with the number of matched properties (*Matched Property Count*) by applying multiple matching criteria to filter the matched properties for each listing[5]. This defined variable provides a more rigorous measure to see for each listing how many similar listing properties are active in the market.

The first Column in Table 2 reports the summary statistics of major variables. Overall, the sold deviation is 6.3%, and the sold price per square foot is 790.9 CAD. *DOM* represents the Days on Market (i.e., the period between the listing date and the sold date, mean = 32). *Age* indicates

[4] Most existing empirical literature adopted the sold price as the dependent variable, for example, see Benefield et al. (2011, 2019), Bian et al. (2023), and Carrillo (2012).
[5] For each property, we consider listing time, property age, location, property size, property value, number of bedroom, and transit score as its matching criteria.

how many years the building is from the built date till the sold date (mean =17). The average assessed value among all listings is 703,825 CAD. Regarding the property features, the average portion of renovated properties, properties with unique views, and luxury properties are 18.8%, 5.1%, and 9.9%, respectively. The average *Matched Property Count* is about 2.6. Among all observations, the average picture count (*Picture Count*) is 14, and the average length of public remarks (*Word Count*) is 67[6].

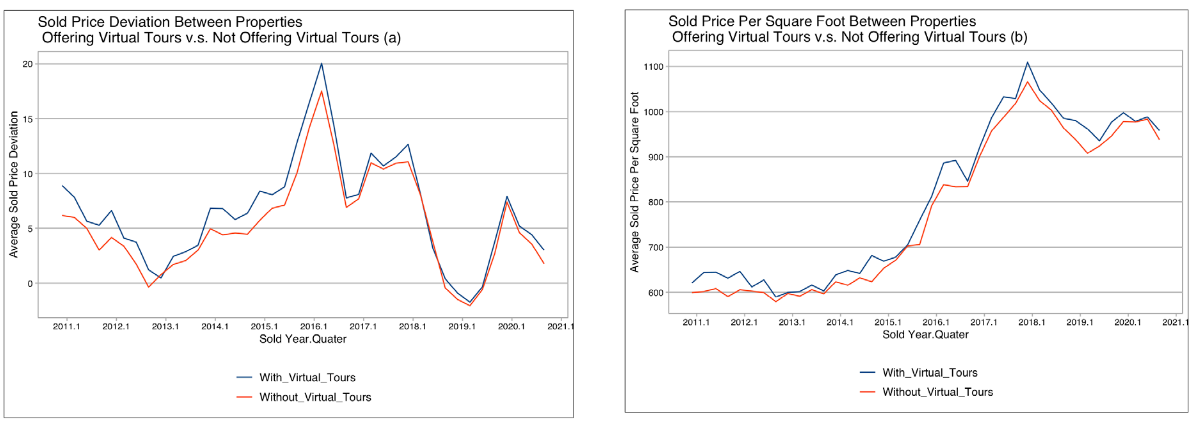
Table 2 provides initial model-free evidence supporting the association of virtual tour offering and sales performance. The second and third Columns display the mean values for properties with and without virtual tours, respectively. The fourth Column reports the p-value of the t-test for the corresponding variable between the two groups. Properties offering virtual tours have significantly higher sold price deviation, sold price per square foot, and shorter days on the market ($p < 0.01$). Furthermore, Figure 3 shows that these differences in sold price deviation and sold price per square foot persist continuously throughout the observation period.

Additionally, Table 2 also indicates that properties offering virtual tours have distinct differences in property features and differentiation levels. Compared to properties without virtual tours, properties offering virtual tours are more likely to be renovated, and be luxurious, and are of significantly lower matched property count ($p < 0.01$). Moreover, properties providing virtual tours have more pictures and longer text descriptions ($p < 0.01$). These findings support our theoretical framework that virtual tour offering is another method of extra information disclosure besides pictures and text, and on average is associated with more favorable sales performance.

[6] To avoid the bias caused by wording style, the length of public remarks is calculated after dropping uninformative stop words and punctuations.

Table 2. Summary Statistics and the Differences in Sales Outcome and Property Features between Properties Offering and Not Offering Virtual Tours

	Total	Without Virtual Tours (*VirtualTour* = 0)	With Virtual Tours (*VirtualTour* = 1)	P-Value
Sold Dev (%)	6.34	6.154	7.01	0.000
Sold Price per SqFt (CAD)	790.977	773.41	854.754	0.000
DOM (days)	31.348	32.408	27.328	0.000
Age (years)	17.015	16.667	18.296	0.000
Assessed Value (CAD)	703,825.30	672,923.20	813,641.90	0.000
Renovation	0.188	0.175	0.234	0.000
View	0.051	0.05	0.054	0.093
Luxury	0.098	0.093	0.116	0.000
Matched Property Count	2.617	2.731	2.2	0.000
Picture Count	13.964	12.947	17.71	0.000
Word Count	66.987	65.051	73.557	0.000



(a) (b)

Figure 3. Time Trend of Differences between Properties Offering and Not Offering Virtual Tours on Sold Price Deviation (a) and Sold Price per Square Foot (b).

Market fluctuation. To control for the potential influence of market fluctuations, we adopted the monthly Sales to Active Listings Ratio (SALR) to capture the real estate market demand and supply fluctuations. SALR evaluates the relative number of sold listings to all listings. A high SALR indicates a relative shortage of listings in the market in which the seller is usually of higher market power. The variety in SALR could affect the price premium and sellers' incentive to offer virtual tours. Figure 4 shows the time trend of the monthly SALR in our dataset. The three peaks of SALR correspond to three typical hot-market periods in Vancouver during the 2nd quarter in

2016, the 2nd quarter in 2017, and the 4th quarter in 2020. We define that the market is hot (*HotMkt* = 1) if the monthly SALR is larger than its median (24.42%).

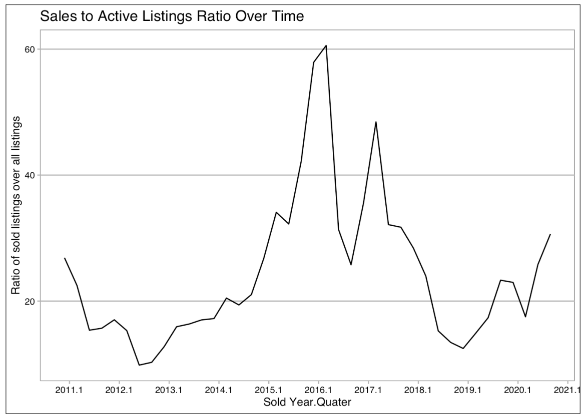


Figure 4. MLS Property Features Published on Typical Online Listing Platform

Table 3 reports the differences in sales outcome and property differentiation level between properties sold on the hot market and non-hot market. The third Column includes the p-value of the two-sample t-test between the group of properties sold during the non-hot market and the hot market. As expected, when the market is hot (i.e., there are relatively more potential buyers compared to the sellers), the sold price deviation (9.1%) and sold price per square foot (880.2) are also remarkably higher than the sold price deviation (3.4%) and sold price per square foot (728.6) when the market is not hot ($p < 0.01$). Noteworthily, there is no significant difference in *Renovation* for properties sold in different market statuses, whereas there are more luxury listings ($p < 0.01$) on the hot market, and the average assessed value is also higher ($p < 0.01$). Another interesting finding is that, in hot markets, the average matched property count is fewer than in the non-hot market ($p < 0.01$). This is because there are generally fewer available listings in the hot market.

Table 3. Differences in Sales Outcome and Differentiated Features between Properties Sold on Hot Market and Non-Hot Market

	***HotMkt* = 0** **(SALR< =median)**	***HotMkt* = 1** **(SALR> median)**	**P-Value**
Sold Dev (%)	3.455	9.89	0.000
Sold Price per SqFt (CAD)	733.848	861.284	0.000
DOM (days)	38.53	22.509	0.000
Age (years)	16.823	17.251	0.0002
Assessed Value (CAD)	676,317.70	737,677.80	0.000
Renovation	0.188	0.188	0.975
Luxury	0.093	0.104	0.000
Matched Property Count	2.928	2.235	0.000

Factors Affecting the Virtual Tour Offering

In order to investigate the factors that influence the offering of virtual tours, we employ reduced-form logit models. In Model 1, we estimate:

$$Prob(Virtual\ Tour_i = 1) = Logit(ln(Assessed\ Value)_i, ln(Matched\ Property\ Count)_i,$$
$$Renovation_i, View_i, Luxury_i, Age_i, SoldYear_i, SoldQuarter_i, SubArea_i, Agent\ Features^7{}_i) \quad (1)$$

In addition, instead of fixing the sold year and sold quarter in Model 1, we include a continuous *YQ Index* that covers the general rising time trend across all 40 year-quarter pairs in our dataset (from 2011 to 2021), along with its quadratic and cubic terms. This allows us to explore the impact of Covid-19 (*Covid*) and the hot market conditions (*HotMkt*) on sellers' choice of offering virtual tours. Specifically, Model 2 estimates:

$$Prob(Virtual\ Tour_i = 1) = Logit(ln(Assessed\ Value)_i, ln(Matched\ Property\ Count)_i,$$
$$Renovation_i, View_i, Luxury_i, Age_i, Covid_i, HotMkt_i,$$
$$YQ\ Index_i, YQ\ Index_i^2,\ YQ\ Index_i^3,\ SubArea_i, Agent\ Features_i) \quad (2)$$

[7] Agent features such as the year of experience are controlled for.

Table 4. Logit Regression Analysis Results for Virtual Tour Offering

	Dependent variable:	
	Virtual Tour (1=offering virtual tours)	
	Model 1	Model 2
	Column (1)	Column (2)
ln (walk score)	0.026	0.028
ln (transit score)	0.392***	0.403***
ln (picture count)	0.818***	0.879***
ln (text length)	0.845***	0.827***
ln(Assessed Value)	0.073	0.020
ln(Total Floor Area)	0.346***	0.379***
Type: Apartment/Condo	0.044	0.039
Type: Townhouse	0.039	0.036
ln(Matched Property Count)	-0.041**	-0.052***
Renovation	0.145***	0.143***
View	0.009	0.012
Luxury	0.138***	0.148***
Age: 5-15	0.109**	0.107**
Age: 15-30	0.081*	0.082*
Age: 30-55	0.118*	0.105*
Age: > 55	-0.046	0.001
Covid (1= after April 1st, 2020)		1.195***
HotMkt (1 = hot market)		-0.073**
YQ_index		-0.024
I(YQ_index2)		0.004***
I(YQ_index3)		-0.0001***
Constant	-1.562	-1.376
Sold Year and Sold Quarter Fixed Effect	YES	NO
Sub-Area Location Fixed Effect	YES	YES
Agent Feature Fixed Effect[8]	YES	YES
Observations	53,063	53,063
Log Likelihood	-24,840.600	-24,744.170
Akaike Inf. Crit.	49,825.210	49,618.340
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 4 summarizes the logit regression outputs. Model 1 suggests that several property characteristics, such as property size ($p < 0.01$), renovations ($p < 0.01$), and luxury features ($p < 0.01$), significantly increase the likelihood of offering virtual tours. Also, the number of similar properties in the market, which is a measure of property uniqueness, shows a significant and negative impact on virtual tour offerings. It means that a listing that has more similar properties in

[8] We fixed agents' features including: agent's year of experience, ratio of previous sold listings being in the same sub area, ratio of previous sold listings being of the same type, etc.

the market is less likely to offer virtual tour. In addition, the results indicate a significant association between other information disclosure (number of pictures and description text length) and the decision to offer virtual tour.

Model 2 supports the robustness of all the above results while introducing the effect of Covid-19 and hot market conditions. Model 2 suggests that after controlling for the market fluctuation and general time trend, there is still a significant positive effect of Covid-19 on the offering of virtual tours, which is consistent with our model-free result displayed in Figure 2. It is also noteworthy that when the real estate market is hot, sellers are less likely to offer virtual tours ($p < 0.01$). This finding may be attributed to the fact that hot markets have fewer available active listings, which reduces search costs and may lower seller motivation to include virtual tours. Conversely, in non-hot markets, there may be more available active listings, increasing search costs and potentially motivating sellers to invest in virtual tours.

Our preliminary analysis highlights the significant differences between properties with and without virtual tours in terms of sales outcomes, such as sold price deviation and sold price per square foot, as well as property features, such as renovation and matched property count. Our model-free analysis indicates that properties offering virtual tours are associated with more favorable sales performance. Furthermore, our initial logistic regression results suggest that sellers' choice to provide virtual tours may be significantly influenced by factors including property features, differentiation levels, and market fluctuations. In the subsequent section, we will examine the impact of offering virtual tours more rigorously using econometric modeling and causal random forest. The potential effects of heterogeneous property features, differentiation levels, and market fluctuations on the relationship between virtual tours and sales outcomes will also be investigated.

IV. Causal Model and Empirical Results

In this section, we investigate the impact of offering virtual tours on the sales performance of properties in the market. To begin with, we demonstrate the correlation among offering virtual tours, other factors, and the sold price of properties. We also acknowledge the challenges of drawing a causal inference in this context. Furthermore, we address the endogeneity issues associated with the offering virtual tour variable by introducing some instrumental variables and also doing robustness check with more recent instrument-free causal inference methods (2sCOPE). We discuss the various sources of endogeneity and how our approach helps to mitigate these concerns. To explore the heterogeneity in the causal effect of virtual tours on sales performance, we extend our model and also employ the causal random forest method. We will elaborate on our findings and discuss their implications.

In evaluating property sales performance in the real estate market, various measures can be considered. While 'sold price per square foot' is commonly used, the government-released assessed value of each property, available annually to buyers and sellers, can offer a more accurate benchmark. The deviation between the sold price and the assessment value (in percentage) captures the performance of the sale more effectively. Unlike listing prices, which can be unreliable, the assessed value serves as a consistent reference point and accounts for unobserved property features not available in MLS data. Thus, using the difference between sold price and assessment value provides a more robust measure for evaluating sales performance.

To model the association between different factors and the target variable (assess dev), we start with a simple linear regression. The results of this regression are shown in Table 5. In Column (1), we control for the fixed effects of time (year and quarter) and location (sub-area of each property). In Column (2), we replace the time fixed effect with another measure, SALR, to control for market conditions at different times. SALR is the sales-to-active-listing ratio in each month and indicates the status of the real estate market. A high SALR (close to 1) indicates a hot market, while a low SALR indicates a cold market.

Our model results show that offering a virtual tour positively correlates with sales performance, measured by the deviation of the sold price from the assessed value, even after accounting for the number of pictures and description length. Luxury and renovated properties exhibit higher deviations than others, while older and more expensive properties struggle to achieve better sales performance. The negative coefficient for 'match count' indicates that common properties with many similar listings (high competition) experience weaker sales performance. In Column (2), the positive SALR coefficient suggests that in a hot market, sold prices tend to exceed assessed values more than in a cold market.

We also include some features of real estate agents to capture their impacts on sales performance. *Agent.YoE* represents the years of experience for listing agents at each transaction time, while *Percent.same.typeDwel* and *Percent.same.sub-area* measure the percentages of past sold properties by each listing agent that had the same type or had been in the same subarea. These two variables indicate the extent to which each listing agent is experienced and familiar with selling the same type of property and in the same subarea. Interestingly, our results show that agent features can significantly impact sales performance, and agents who list properties similar to their previous selling experiences tend to perform better in terms of the deviation of sold price from the assessed value.

Although our findings in Table 5 suggest a positive and significant association of offering virtual tour and sales performance for a listed property, it is challenging to infer a causal relationship based on this analysis. The virtual tour dummy variable is likely endogenous, as sellers or their agents may strategically decide to disclose additional information and to offer virtual tours. Equation (4) captures the general specification for the impact of virtual tours (τ), with X_i representing observed property and agent features. However, the virtual tour variable may be correlated with the error term ($cor\ (virtual\ tour_i, \varepsilon_i) \neq 0$ due to unobserved factors influencing the decision to offer a virtual tour. Consequently, the estimated coefficient of virtual tour may not be an unbiased estimate for the impact of virtual tours on sales performance.

$$Assess\ dev_i = \beta * X_i + \tau * virtual\ tour_i + \varepsilon_i \tag{4}$$

Table 5. Regression Analysis Results for the factors affect the sales performance

	Dependent variable:	
	Assess Dev	
	Column (1)	Column (2)
ln (walk score)	0.852**	0.669*
ln (transit score)	1.968***	2.925***
ln (picture count)	0.394***	0.574***
ln (text length)	1.112***	1.130***
Virtual tour	**0.805*****	**0.722*****
Renovation	2.018***	1.744***
TypeDwel (Apartment/Condo)	-1.363***	-0.848***
TypeDwel (Townhouse)	-1.656***	-0.925***
ln (Age)	-1.398***	-0.633***
ln (Assess value)	-10.206***	-6.917***
ln(TotFlArea)	10.283***	3.955***
ln(Matched Property Count)	-1.274***	-1.779***
Percent same typeDwel	0.238**	0.304***
Percent same sub-area	0.834***	0.728***
Agent YoE	0.022	0.079**
View	0.062	-0.094
Luxury	1.528***	1.228***
Log (SALR)		8.858***
Constant	85.757***	30.005***
Sold Year-Quarter Fixed Effect	**YES**	**No**
Sub-Area Location Fixed Effect	**YES**	**YES**
Observations	55,343	55,136
R2	0.238	0.223
Adjusted R2	0.237	0.222
Note:	*p<0.1; **p<0.05; ***p<0.01	

To address the endogeneity issue, we employ instrumental variables (Z_i) that meet two key criteria: they must significantly influence the likelihood of offering a virtual tour (relevance condition) and be uncorrelated with the error term in equation (4), conditional on other covariates (exclusion condition). This ensures that the instrument affects sales performance solely through its impact on the decision to offer a virtual tour.

We propose two instrumental variables that are likely to influence real estate agents' decisions to offer virtual tours (relevance condition) without directly affecting the sales performance of the listing (exclusion condition). As agents typically manage all aspects of a property listing, these instruments are well-suited to isolate the effect of virtual tours. Let's consider the two variables defined below.

$$\boldsymbol{AgentPastVtour_i}: precentage\ of\ past\ sold\ properites\ with\ virtual\ tour\ by\ agent\ of\ listing\ i$$

$$\boldsymbol{TeamVtour_i}: precentage\ of\ past\ sold\ properites\ with\ virtual\ tour\ by\ \boldsymbol{teammates}\ of\ listing\ i's\ agent$$

Offering virtual tour for a new listing in the market needs time and effort by agents. We can assume that if an agent had more experience before on building virtual tours, it could be more convenient and less costly for that agent to offer the virtual tour for his current listing. So, we expect $\boldsymbol{AgentPastVtour_i}$ to have a significant impact on the agent's decision to offer virtual tour for the current listing (relevance condition). However, if we control for other factors (X_i) of the current listing i, we shouldn't expect a direct effect of past experience of the agent in offering virtual tour on the sales performance of current listing i (exclusion condition).

Additionally, each realtor works for a brokerage office, and while the office itself may not impact sales performance, agents within the same office can build networks and support each other. We believe an agent's colleagues may influence their decision to offer virtual tours. For example, if an agent's colleagues frequently use virtual tours, the agent is more likely to do the same due to word-of-mouth and networking effects. However, it is unlikely that the colleagues' use of virtual tours directly impacts the agent's sales performance for a listing.

Using the two instruments introduced above, we run a two-stage least squares (2SLS) model to address the endogeneity issue of the *virtual tour* dummy variable in our analysis.

In the first stage, we estimate the probability of offering a virtual tour for the listing i using a logistic regression model as follows:

$$\Pr(virtual\ tour_i) = logit\ (\beta * X_i + \alpha * Z_i) \tag{5}$$

Where,

$$X_i = (walkscore_i, transitscore_i, PicCount_i, TextLength_i, year_i, quarter_i, subarea_i, TypeDwel_i, renovation_i, Property\ Age_i, assess\ value_i, TotFlArea_i, matchcount_i, percentSameTypeDwel_i, percentSameSA_i, Luxury_i, View_i)$$

$$Z_i = (\boldsymbol{AgentPastVtour_i}, \boldsymbol{TeamVtour_i}) \tag{6}$$

In the second stage, we run Model (4) discussed above by considering the predicted probability of offering virtual tour ($\widehat{pr}(virtual\ tour)$) estimated from specification (6) instead of using actual observed value of virtual tour dummy. So, we have:

$$assess\ dev_i = \beta * X_i + \tau * \widehat{pr}(virtual\ tour_i) + \varepsilon_i \tag{7}$$

Table 6 presents the estimated coefficients for the first and second stages of the 2SLS analysis. In stage (1), the coefficients of instruments ($\boldsymbol{AgentPastVtour_i}, \boldsymbol{TeamVtour_i}$**)** are both positive and significant which indicates that the two instruments are strong predictors of offering virtual tour. The positive and statistically significant coefficient of virtual tour in the second stage suggests that even after accounting for the use of instruments, offering virtual tours has a positive and significant impact on sales performance. This indicates that if the two conditions of relevance and exclusion for the defined instruments are met, there is evidence to support the claim that offering virtual tours can have a causal, positive effect on sales performance, leading to an increase in sales price of around 0.64%. In other words, for a property with an assessed value of 1 million dollars, offering a virtual tour could result in an average increase in sold price of approximately $6,400.

Table 6. 2SLS Regression results to capture the impact of offering virtual tour on sales performance

	Stage (1) Dependent variable: **Virtual Tour**	Stage (2) Dependent variable: **Assess Dev**
	Column (1)	Column (2)
ln (walk score)	-0.022	0.763**
ln (transit score)	0.445**	1.734***
ln (picture count)	0.771***	0.365***
ln (text length)	0.430***	0.985***
Predicted virtual tour		**0.637*** **
ln(Assessed Value)	0.359***	-11.636***
ln(Matched Property Count)	0.005	-1.384***
Renovation	0.280***	2.655***
View	-0.047	-0.076
Luxury	0.172***	1.599***
Age: 5-15	0.055	-0.255**
Age: 15-30	0.049	-1.343***
Age: 30-55	-0.059	-2.418***
Age: > 55	-0.128	-2.215***
percentSameTypeDwel	-0.941**	0.215*
percentSameSA	-0.146***	0.812***
ln(TotFlArea)	0.410***	13.073***
AgentPastVtour	**4.210*** **	
TeamVtour	**1.977*** **	
Constant	-6.329	76.619***
List Year and List Quarter Fixed Effect	YES	YES
Sub-Area Location Fixed Effect	YES	YES
Agent Feature and property type Fixed Effects	YES	YES
Observations	52841	52841
Log Likelihood	-20730.84	R^2: 0.232
Akaike Inf. Crit.	41601.69	
Note:	*p<0.1; **p<0.05; ***p<0.01	

Robustness Check with 2sCOPE. While we present various institutional background and evidences in choosing the instrumental variables in this section, we face the same challenge as most empirical research that the IV exclusion restriction cannot be proven or tested. In this subsection, we present robustness analyses using an IV-free causal inference method, namely the Two-stage Copula estimation (2sCOPE) (Yang et. al. 2022).

The 2sCOPE method builds on the strand of literature pioneered by Park and Gupta (2012), where the statistical properties of copula transformations lend to convenient controls of endogeneity in the absence of instrumental variables. If we think of 2SLS as bringing external exogenous variations in the IVs to tease out the exogenous part of the virtual tour treatment, then the 2sCOPE is leveraging the observed exogenous control covariate(s) to wash out the endogenous part of the virtual tour treatment. This is done through regressing its copula transformation of the virtual tour variable on the copula transformed terms of the exogenous covariates. We then include the residual term from this first-stage copula regression to the second-stage panel analyses that we discussed in Equation (4). We report the analyses results below in Table 7.

Table 7. 2sCOPE Analysis Results for the virtual tour effect on the sales performance

	Dependent variable:	
	Assess Dev	
	Column (1)	Column (2)
ln (walk score)	-0.051	0.042
ln (transit score)	1.342***	0.932***
ln (picture count)	0.524**	0.547**
ln (text length)	0.836***	0.797***
Virtual tour	**0.618****	**0.690****
Renovation	2.987***	3.021***
TypeDwel (Apartment/Condo)	-1.354***	-0.780***
TypeDwel (Townhouse)	-1.666***	-1.012***
ln (Age)	-1.390***	-0.604***
ln (Assess value)	-11.873***	-6.431***
ln(TotFlArea)	11.420***	4.908***
ln(Matched Property Count)	-1.190***	-1.662***
Percent same typeDwel	0.293***	0.301***
Percent same sub-area	0.653***	0.493***
Agent YoE	0.016	0.099***
View	0.129	-0.113
Luxury	1.462***	1.170***
Log (SALR)		8.806***
Stage 1 resid	-.080	-.070
Constant	62.629***	61.428***
Sold Year-Quarter Fixed Effect	**YES**	**No**
Sub-Area Location Fixed Effect	**YES**	**YES**
Observations	55,656	55,655
R2	0.214	0.209

Adjusted R2	0.213	0.208
Note:	*p<0.1; **p<0.05; ***p<0.01	

We observe that the results are largely consistent with those presented in Table 5 and 6, and virtual tour takes highly statistically significant coefficients in predicting the deviation of sold price from the assessed value (dependent variable).

Heterogeneity. We have extended Model (7) by introducing interaction terms to capture the heterogeneity of treatment effects across various groups and show the results in Table 8. In Column (1), we present the estimation results of Model (7) by incorporating the interaction between *Virtual tour* and *Renovation*. The positive and significant coefficient of the interaction term indicates that the impact of offering virtual tours on sales performance is greater for renovated properties (p-value <0.1). In Column (2), we examine the heterogeneity of the treatment (Virtual tour) effects across different property age groups. The results show that the effect of providing virtual tours on sales performance is higher for mid-age properties (35-50 years old). We will discuss the possible mechanisms that may explain this finding later. Our extended model, presented in Column (3), which takes into account of the interaction between *virtual tours* and *View*, finds a significant difference in the impact of offering virtual tours on sales performance between properties with ocean views compared to others. For the properties with ocean/sea view, the effect of offering virtual tour is significantly higher than properties without views.

Table 8. Heterogeneity in the Effect of Virtual Tours on Sales Performance

	Stage 2 estimation with heterogeneity Dependent variable: Assess Dev		
	Renovation	**Property age**	**View**
	Column (1)	Column (2)	Column (3)
Predicted virtual tour	**0.305***	**0.188***	**0.233***
Renovation	2.617***	2.651***	2.658***
Vtour*Renovation	**0.818****		
ln(Matched Property Count)	-1.394***	-1.395***	-1.388***
View	0.353**	0.353**	0.111
Vtour*View			**0.976****
TypeDwel (Apartment/Condo)	-1.680***	-1.674***	-1.679***
TypeDwel (Townhouse)	-1.679***	-1.677***	-1.683***
Age: 5-15	-0.325**	-0.389**	-0.304**
Age: 15-30	-1.446***	-1.503***	-1.450***
Age: 30-55	-2.651***	-2.964***	-2.656***
Age: > 55	-2.221***	-2.610***	-2.218***
Vtour*Age: 5-15		**0.436**	
Vtour*Age: 15-30		**0.349**	
Vtour*Age: 30-55		**1.335****	
Vtour*Age: > 55		**0.979**	
ln(Assessed Value)	-11.222***	-11.226***	-11.225***
ln(TotFlArea)	12.647***	12.650***	13.044***
percentSameTypeDwel	0.257**	0.256**	0.257**
percentSameSA	0.664***	0.664***	0.667***
Agent YoE	-0.02	-0.02	-0.02
Luxury	1.615***	1.608***	1.598***
Constant	71.039***	71.070***	71.068***
Sold Year-Quarter Fixed Effect	**YES**	**YES**	**YES**
Sub-Area Location Fixed Effect	**YES**	**YES**	**YES**
Observations	52841	52841	52841
R2	0.231	0.231	0.231
Adjusted R2	0.23	0.23	0.23
Note:	*p<0.1; **p<0.05; ***p<0.01		

In the 2SLS approach described by Models (6) and (7), we control for year- and quarter-fixed effects. However, this means we cannot identify the impact of market conditions (hot/cold market) on offering virtual tours and sales performance, as there is no variation in the *SALR* variable once the fixed effects of year and quarter are considered. To address this issue and identify the impact of *SALR*, which is time-varying, on offering virtual tours and sales performance, we used a polynomial function to control for time trends instead of relying on the fixed effects of year and quarter.

Table 9 presents the results of our 2SLS approach for identifying the impact of virtual tours on sales performance when we use a polynomial function to control for time trends instead of fixed effects. To do this, we defined *YQ_index* as a numeric variable ranging from 1 to 43, which indicates the year-quarter of each sold property. By including a polynomial function of *YQ_index*, we are able to control for time trends while running the 2SLS approach. The results in Table 9 are consistent with those in Table 6, showing a positive and significant impact of offering virtual tours on sales performance. Additionally, we observe a negative and significant coefficient for *HotMkt* in Stage (1), indicating that agents are less likely to offer virtual tours when the market is hot (*SALR* > median). In Stage (2), we find that the deviation of sold price from assessed value (*Assess Dev*) is significantly higher when the market is hot, as expected.

Table 9. 2SLS Regression results to capture the impact of offering virtual tour on sales performance ***with functional form for time trends***

	Stage (1) Dependent variable:	Stage (2) Dependent variable:
	Virtual Tour	**Assess Dev**
	Column (1)	Column (2)
ln (walk score)	-0.015	0.750*
ln (transit score)	0.449***	1.950***
ln (picture count)	0.830***	0.843***
ln (text length)	0.416***	0.927***
Predicted virtual tour		**0.762*****
ln(Assessed Value)	0.452***	-10.335***
poly(YQ_index, degree = 4)1	94.795***	321.829***
poly(YQ_index, degree = 4)2	52.672***	-422.343***
poly(YQ_index, degree = 4)3	53.580***	-334.467***
poly(YQ_index, degree = 4)4	55.505***	357.438***
HotMkt	-0.204***	3.446***
ln(Matched Property Count)	-0.005	-1.530***
Renovation	0.254***	2.597***
View	-0.051	0.271
Luxury	0.155***	1.479***
Age: 5-15	0.065	-0.111**
Age: 15-30	0.075*	-1.062***
Age: 30-55	-0.028	-2.026***
Age: > 55	-0.098	-1.728***
Agent experience	-0.018**	0.042*
percentSameTypeDwel	-0.043	0.435***
percentSameSA	-0.152***	0.659***

Ln(TotFlArea)	0.309***	11.467***
AgentPastVtour	**4.204*** **	
TeamVtour	**2.018*** **	
Constant	-6.306	67.970***
Sub-Area Location Fixed Effect	YES	YES
Agent Feature and property type Fixed Effects	YES	YES
Observations	52841	52841
Log Likelihood	-20845.46	R2: 0.212
Akaike Inf. Crit.	41816.92	Adjusted R2: 0.211
Note:	*p<0.1; **p<0.05; ***p<0.01	

To capture possible heterogeneous treatment effects of offering virtual tours on sales performance in hot versus cold markets and based on the number of matched properties, we extend the results in Table 9 by adding interactions of *HotMkt* and *ln(Matched Property Count)* with *Virtual Tour* in Stage (2). Table 10 shows the results of extended model with heterogenous treatment effects. Our findings suggest that the impact of offering virtual tours on sales performance can vary depending on the market situation and property uniqueness. Specifically, our findings show that for a unique property listed in a cold (buyer) market, the effect of offering a virtual tour on sales performance is smaller and only marginally significant. However, the positive and significant coefficient for the interaction between *HotMkt* and *Vtour* suggests that offering virtual tours can be more effective in a hot market. Additionally, our results indicate that offering virtual tours for properties with a higher number of matched properties (common properties) in the market could have a larger impact on sales performance.

Table 10. Extended Model Results to Capture Heterogeneity in the Effect of Virtual Tours on Sales Performance for Market Hotness and Property Uniqueness

	Stage 2 estimation with heterogeneity **Dependent variable: Assess Dev**
	Market hotness and property uniqueness
	Column (1)
ln (walk score)	0.752*
ln (transit score)	1.944***
ln (picture count)	0.841***
ln (text length)	0.930***
Predicted virtual tour	**0.420***
HotMkt	**3.338*** **
Vtour* HotMkt	**0.434** **

Renovation	2.597***
ln(Matched Property Count)	**-1.461*****
Vtour* ln(Matched Property Count)	**0.363***
View	0.273
ln(Assessed Value)	-10.351***
ln(TotFlArea)	11.473***
PercentSameTypeDwel	0.438***
PercentSameSA	0.659***
Luxury	1.479***
Constant	66.132***
Polynomial time trends	**YES**
Sub-Area Location Fixed Effect	**YES**
Property age groups Fixed Effects	**YES**
Observations	52841
R2	**0.208**
Adjusted R2	**0.207**
Note: *p<0.1; **p<0.05; ***p<0.01	

Causal Random Forest to Capture Heterogeneity. In this subsection, we use the causal random forest method (Athey and Wager 2018) to infer the heterogeneity in the causal impact of offering virtual tours on sales performance. This method combines random forests, a machine learning technique, with causal inference to estimate treatment effects. It handles high-dimensional covariates, where traditional regression struggles with nonlinearity and interactions. Athey et al. (2019) extended this to generalized causal random forests (GRF), addressing endogeneity with instrumental variables. We use the same instruments as before, ($\boldsymbol{AgentPastVtour_i}, \boldsymbol{TeamVtour_i}$). GRF provides a powerful way to understand the heterogeneity in the causal effects of virtual tours, complementing our other methods for a comprehensive analysis.

The estimated results show that the average treatment (offering virtual tour) on sales performance is positive and significant (ATE = 0.767 and std.error (ATE) = 0.096) which is consistent with what we found based on classical econometric approaches. The calibration test result in Table 11 also suggests that heterogeneity exists in the conditional average treatment effects. The GRF approach estimate the treatment effect at the individual level which means that for each observation (given X_i), we can get the estimated conditional treatment effect. Figure 5 shows the histogram of estimated CATE for each individual. Figure 5 suggests that the treatment effects have variation among individual observations, so the impact of offering virtual tour on sales performance could be very different across listings with different features (X_i).

Table 11. Calibration Test results for Causal Random Forest

	Estimate	**Std. Error**	**Pr(>t)**
Mean.Forest.Prediction	1.00715	0.17116	2.011e-09 ***
Differential.Forest.Prediction	0.63155	0.25908	0.007393 **

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

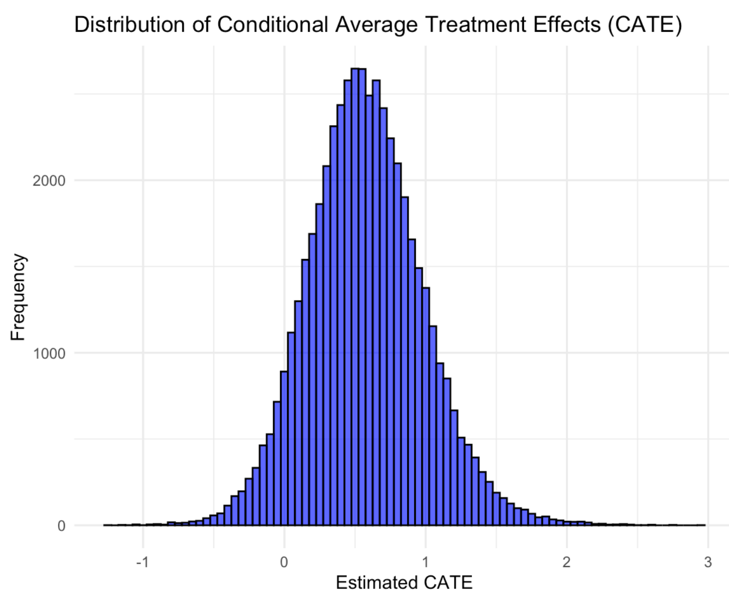


Figure 5. Heterogeneity in the estimated conditional treatment effects

Using the estimated treatment effects at the individual level, we can compare the CATE estimates across different groups. First, we examine how the average CATE estimates are different after Covid compared to before it. As we discussed in the data section, Figure 2 clearly shows that right after Covid exposure and lockdowns, there is significant spike in offering virtual tours and more than 50% of listed properties offered virtual tours. Figure 6 below shows the average treatment effects on offering virtual tour on sales performance based on causal random forest in the period of 6 months after starting Covid compared to the six months period before starting Covid. The results show that the effectiveness of offering virtual tour on sales performance is lower after starting Covid compared to what it was before. Since virtual tour feature has become a more common feature (more than 50% properties offer it) after Covid, it is no longer a salience feature for a listing. Therefore, cognitive salience may explain the diminishing effectiveness of it on sales performance.

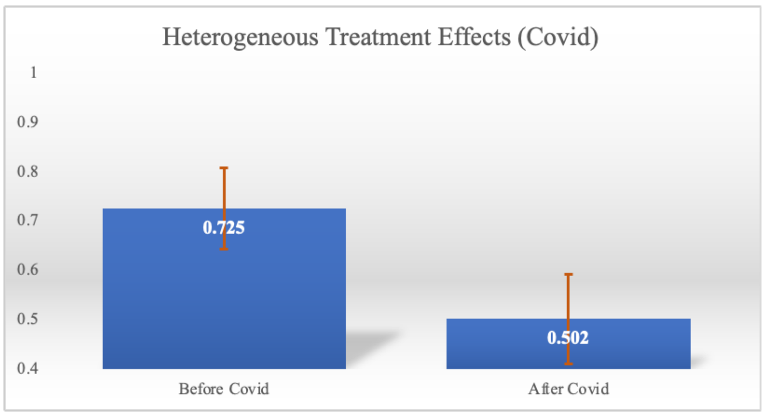


Figure 6. Heterogeneity in the estimated conditional treatment effects ***after versus before Covid***

To better examine the moderating effects of cognitive salience on the impact of offering virtual tour on sales performance, we define a more rigorous measure as below:

$$\boldsymbol{similaractiveVTpercent_i}: The\ percentage\ of\ similar\ active\ listings\ of\ property\ i\ in\ the\ market\ with\ virtual\ tour$$

By this definition, for each property i, we calculate the percentage of similar properties in the market at the same time (based on the same criteria we defined before to find the matched properties) with offering virtual tour. In this way, higher value of $similaractiveVTpercent_i$ means that offering virtual tour for property i is not a salient feature because more similar properties have virtual tour at that time. We now consider the interaction term of $similaractiveVTpercent$ and $\widehat{pr}(virtual\ tour_i)$ in Model (7) following the 2SLS model to capture the heterogeneous effects of offering virtual tour on sales across different levels of offering virtual tours for similar properties, Table 12 shows the results of this specification.

Table 12. 2SLS Regression results to capture the moderating impact of salient feature on the effect of offering virtual tour on sales performance

	Stage (1) Dependent variable: **Virtual Tour**	Stage (2) Dependent variable: **Assess Dev**
	Column (1)	Column (2)
ln (walk score)	-0.022	0.760**
ln (transit score)	0.445**	1.741***
ln (picture count)	0.771***	0.363***
ln (text length)	0.429***	1.079***
Similar virtual tour %	**0.021***	**0.035**
Predicted virtual tour		**0.897*****
Vtour * similarVtour%		**-0.231****
ln(Assessed Value)	0.363***	-11.636***
ln(Matched Property Count)	0.005	-1.433***
Renovation	0.280***	2.655***
View	-0.047	-0.076
Luxury	0.172***	1.599***
Age: 5-15	0.055	-0.255**
Age: 15-30	0.049	-1.343***
Age: 30-55	-0.059	-2.418***
Age: > 55	-0.128	-2.215***
percentSameTypeDwel	-0.125**	0.217*
percentSameSA	-0.102*	0.815***
ln(TotFlArea)	0.297***	12.812***
AgentPastVtour	**4.129*****	
TeamVtour	**1.816*****	
Constant	-6.277	75.971***
List Year and List Quarter Fixed Effect	YES	YES
Sub-Area Location Fixed Effect	YES	YES
Agent Feature and property type Fixed Effects	YES	YES
Observations	50764	50764
Log Likelihood or R^2	LL: -19730.84	R^2: 0.232
Akaike Inf. Crit.	39601.69	

Note: *p<0.1; **p<0.05; ***p<0.01

The results in Table 12 indicate that whether offering virtual tour as a salient feature among other similar competing properties in the market could significantly affect the effectiveness of offering virtual tour on the sales performance. In other words, our results show that when the higher percentage of similar active listings in the market have virtual tours, the impact of offering virtual tour for a listing on sales performance is significantly lower.

As discussed earlier, Causal Random Forest (GRF) provides estimates of Conditional Average Treatment Effects (CATE) at the individual level. This approach enables us to gain a more detailed understanding of heterogeneity in the treatment effect (impact of virtual tours) based on various factors. To explore the sources of this heterogeneity, we fit a regression model using the estimated individual treatment effects ($\widehat{\tau_i}$) as the outcome variable and several property and agent characteristics as covariates:

$$\hat{\tau}_i = X_i \gamma + \varepsilon_i \qquad (8)$$

where $X_i =$

$$(Year_i, Renovation_i, Property\ Age_i, Assess\ value_i, Matchcount_i, PercentSameTypeDwel_i,$$

$$PercentSameSA_i, AgentYearsExperience_i, View_i, SimilaractiveVTpercent_i)$$

The estimated coefficients of Model (8) indicate how listings with different characteristics respond differently to the inclusion of a virtual tour. In other words, this model allows us to capture the contribution of these factors to the heterogeneity of the virtual tour's treatment effect, after accounting for potential endogeneity with the plausibly exogenous IVs. This provides a comprehensive understanding of which factors moderate the effectiveness of offering virtual tours on sales performance.

Table 13 presents the estimation results of Model (8) using Weighted Least Squares (WLS) to account for the varying precision of the treatment effect estimates obtained from the Causal Random Forest (GRF). By using the inverse of the estimated standard errors of individual treatment effects ($se(\hat{\tau}_i)$) as weights, the WLS approach ensures that more precise estimates are given higher importance in the regression. This methodology allows us to capture the heterogeneous impacts of virtual tours on sales performance across different property and agent characteristics.

The coefficients in Table 13 highlight the significance of various moderating factors. For instance, the positive and significant coefficient of *Renovation* suggests that virtual tours are more effective for properties that have undergone renovations compared to those that have not. In contrast, the negative coefficient for *Sold Year* indicates that the effectiveness of virtual tours has declined over time, implying that virtual tours might have lost some of their novelty effect. Age-related heterogeneity is also observed: properties with mid-range ages (30-55 years) experience a stronger positive impact from virtual tours. This suggests that mid-aged properties might benefit more from virtual tours. Additionally, the negative coefficient for *similarVtour%* implies that virtual tours are more impactful when a lower percentage of similar properties have them. This finding emphasizes the importance of differentiation and the salience of the virtual tour in a competitive market.

Market conditions also play a significant role. The positive coefficient for ln(*SALR*) (Sales-to-Active Listings Ratio) suggests that the effectiveness of virtual tours is higher in hotter markets, while a higher *Matched Property Count* increases the effectiveness of virtual tours, indicating that virtual tours are particularly beneficial in markets with greater competition.

Agent characteristics further moderate the impact of virtual tours. The negative and significant coefficient for *Agent Years of Experience* suggests that junior agents (less experienced) gain more from using virtual tours than senior agents. Similarly, the negative coefficient for *PercentSameSA* indicates that agents who typically list and sell properties in the same sub-area might see less benefit from virtual tours, potentially due to over-familiarity with the market. In contrast, the positive coefficient for *PercentSameTypeDwel* suggests that agents with more experience selling a specific type of property (e.g. apartment vs townhouse) can leverage virtual tours more effectively for that category.

Overall, these results indicate that the heterogeneity in virtual tour effectiveness is driven not only by property and market characteristics but also by agent experience and specialization, highlighting the nuanced and multifaceted role of virtual tours in enhancing sales performance.

Table 13. Estimation Results to Capture Heterogeneity in the Effect of Virtual Tours on Sales Performance in Model (8)

	Dependent variable: Treatment effect ($\hat{\tau}_i$)
	Moderating impacts of different factors on virtual tour effectiveness
Sold.year	-0.0175***
ln (Assessed Value)	0.1531***
Renovation	0.1965***
ln (Text Length)	0.0661***
View	0.0063*
ln (SALR)	0.1072***
similarVtour%	-0.0013***
ln(Matched Property Count)	0.0051**
Age: 5-15	0.0337**
Age: 15-30	0.0212**
Age: 30-55	0.0762***
Age: > 55	0.0436*
PercentSameTypeDwel	0.1903***
PercentSameSA	-0.0604***
AgentYearsExperience	-0.0258***
Constant	3.3102***
Observations	50,965
R2	**0.187**
Adjusted R2	**0.185**
Note:	*p<0.1; **p<0.05; ***p<0.01

The heterogeneous results remain robust in the 2sCOPE specifications too. In the next section, we discuss some possible mechanism could potentially explain our heterogeneous findings.

V. Discussion

The findings of this study offer valuable insights into the impact of offering virtual tours and providing additional property information in the real estate market. Our research establishes that virtual tours have a significantly positive effect on sales performance, even after accounting for various sources of unobserved endogeneity, including property features, transaction timing, location, and agent characteristics. This provides strong evidence that virtual tours can causally influence increased sales performance, rather than being driven by external confounding factors.

A key contribution of our paper is the comprehensive examination of heterogeneity in the effectiveness of virtual tours and the consideration of potential theoretical mechanisms that explain these effects. We find that the impact of virtual tours is not uniform and is significantly moderated by various property and market characteristics. For instance, virtual tours are less effective for more differentiated and unique properties with fewer matched properties. This suggests that virtual tours are particularly beneficial when buyers face high search costs due to a greater number of comparable alternatives in the market. This insight emphasizes the importance of utilizing virtual tours as a tool to reduce buyer uncertainty and enhance decision-making, especially in competitive markets.

Additionally, the study identifies that virtual tours are more effective for properties in the mid-age range (30-50 years old), where buyers typically face higher uncertainty regarding the property's quality and condition. For these properties, virtual tours help reduce search costs and provide clarity, leading to better sales outcomes.

More importantly, we observe that the effectiveness of virtual tours has declined over time, particularly after the COVID-19, with the increased adoption and popularity of virtual tours during and after the pandemic. One plausible explanation for this decline is that virtual tours have become a standard feature, diminishing their novelty and competitive advantage. Our findings, supported by the analysis of similar listings, show that when a higher percentage of comparable properties have virtual tours, the effectiveness of offering a virtual tour decreases. This result aligns with the cognitive salience theory in advertising, indicating that virtual tours no longer stand out and, therefore, do not provide the same differentiation benefit they once did. From a managerial perspective, this suggests that real estate agents and sellers should strategically use virtual tours and potentially combine them with other innovative features to maintain a competitive edge.

Furthermore, our results show that the effectiveness of virtual tours is higher in hot real estate markets, where conditions resemble an auction market (characterized by high sales-to-active listings ratios). The unraveling theory may explain why virtual tours are more impactful in these settings. In hot markets, where there is high demand and competition among buyers, virtual tours can help listings stand out, attract attention, and accelerate decision-making. However, in colder markets, where buyer engagement is lower, offering virtual tours may overwhelm potential buyers, reducing their effectiveness. This highlights the strategic value of timing and market context when using virtual tours to maximize their impact on sales performance.

In terms of agent characteristics, our study finds significant heterogeneity in the effect of virtual tours based on agent experience. Junior agents, with fewer years of experience and less familiarity with the market, benefit more from offering virtual tours compared to senior agents. This suggests that virtual tours can serve as a compensatory tool, providing less experienced agents with a competitive advantage that helps boost their listings' performance and narrow the gap with more experienced agents. Thus, real estate agencies may find virtual tours to be a valuable asset in training and supporting junior agents.

From a managerial perspective, our findings highlight the potential value of strategically deploying virtual tours to maximize their impact. Given the declining effectiveness over time, virtual tours may be more impactful when used selectively and in combination with other innovative features to enhance differentiation in competitive markets. They are most effective for properties facing high buyer uncertainty (e.g., mid-aged homes) or in hot markets with intense competition, where they can help listings differentiate and attract attention. Additionally, virtual tours can be a compensatory advantage for junior agents, enhancing their ability to compete with more experienced professionals.

This study has several limitations that could be addressed in future research. First, we do not observe online engagement metrics, such as page views or time spent on listings, which could provide deeper insights into the role of virtual tours in the buyer decision process. Future research could investigate whether virtual tours impact both initial buyer engagement (online behavior) and subsequent offline actions (e.g., property visits). Second, while our use of instrumental variables (IVs) and alternative causal inference methods strengthens the causal validity of our findings, exploring new and more robust instruments could further enhance the reliability of the results.

Overall, our study serves as a stepping stone for future research by offering a detailed understanding of how virtual tours influence sales performance and the role of heterogeneity across different property, market, and agent characteristics. Most importantly, our findings demonstrate that the effectiveness of virtual tours is not static but has evolved over time, becoming less impactful as they have become a standard feature in the market. This emphasizes the need for continuous innovation and strategic deployment of virtual tours to sustain their effectiveness and value in the real estate industry.

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