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Effect of View Counts and Favorites on Product Price-- Preliminary Evidence from the Housing Market

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ABSTRACT

This study is about empirically investigating the impact on home prices attributable to information buyers and sellers share in real estate portals such as Zillow.com and Redfin.com. Theories of information economics suggest that more information leads to more advantages in negotiations or favorable terms. However, when both buyers and sellers are informed from these sources, who gains the upper hand remains unclear and this question remains unexplored in the literature. Specifically, this study poses the research questions: what is, if any. the net effect on price when property related information is shared in online portals. A regression model estimated using a data set of 200 transactions in Orange County, California, drawn from Redfin.com and Zillow.com, showed evidence of net positive effect of online information on selling price, after controlling for basic housing characteristics and related explanatory variables.

Key words: Online consumer behavior, information asymmetry, housing market, days on the market.
JEL Classification: D82, R31,

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1. INTRODUCTION

With the advent of e-commerce, retailers gained access to real-time purchase and search behavior of customers. This access allowed some companies to engage in dynamic pricing, where prices could fluctuate based on customer traffic and demand. However, this one-sided information advantage initially enjoyed by sellers diminished as more and more online portals and price comparison sites emerged, offering increased information access to buyers. As information-sharing portals proliferated across various product and service categories, the internet democratized access to information, empowering both buyers and sellers in negotiations. This often leads to a better outcome for the party with the more accurate and up-to-date information, as seen in price matching strategies by retailers like Best Buy. Consumers today are more empowered by information than ever before (Wilkinson, 1998; Perkins and Zimmerman, 1995).

Real estate buyers have a stronger incentive to search for information online prior to making offers. Furthermore, prospective buyers also share information about their preference that can be viewed by the public. About 90% of homebuyers searched online during their home buying process and real estate search in Google surged 253% in the last 4 years (National Association of Realtors and Google, 2013). Online information portals (e.g., Zillow.com, Redfin.com) have democratized access to information that was once only available through the help of real estate agents. Although the theories of information economics (e.g., Stiglitz, 2008; Spence, 1973) predict that more information means more financial advantage in a transaction, it is not clear who is more empowered—the buyers or the sellers. Both buyers and sellers are expected to take into account all publicly available information, especially from the portals. In addition to disseminating basic facts about properties, these portals also facilitate sharing of user generated information such as "favorites," "number of views," and open house information. Yet, the literature on real estate pricing has largely ignored the effect this information sharing on purchase price. Buyers glean clues about sellers' equity in the house, price history, number of days on the market, and house characteristics. Of particular interest to sellers are how many times a listing is viewed by prospective buyers and how many buyers saved the listed property as their favorites, a metric akin to "Like" on Facebook.com. With this study the main research question to answer is this: what is the effect on price of information shared in online real estate portals? If there is a positive effect of views and favorites on selling price, that is indicative of home sellers having advantage over buyers, and the converse also shall follow.

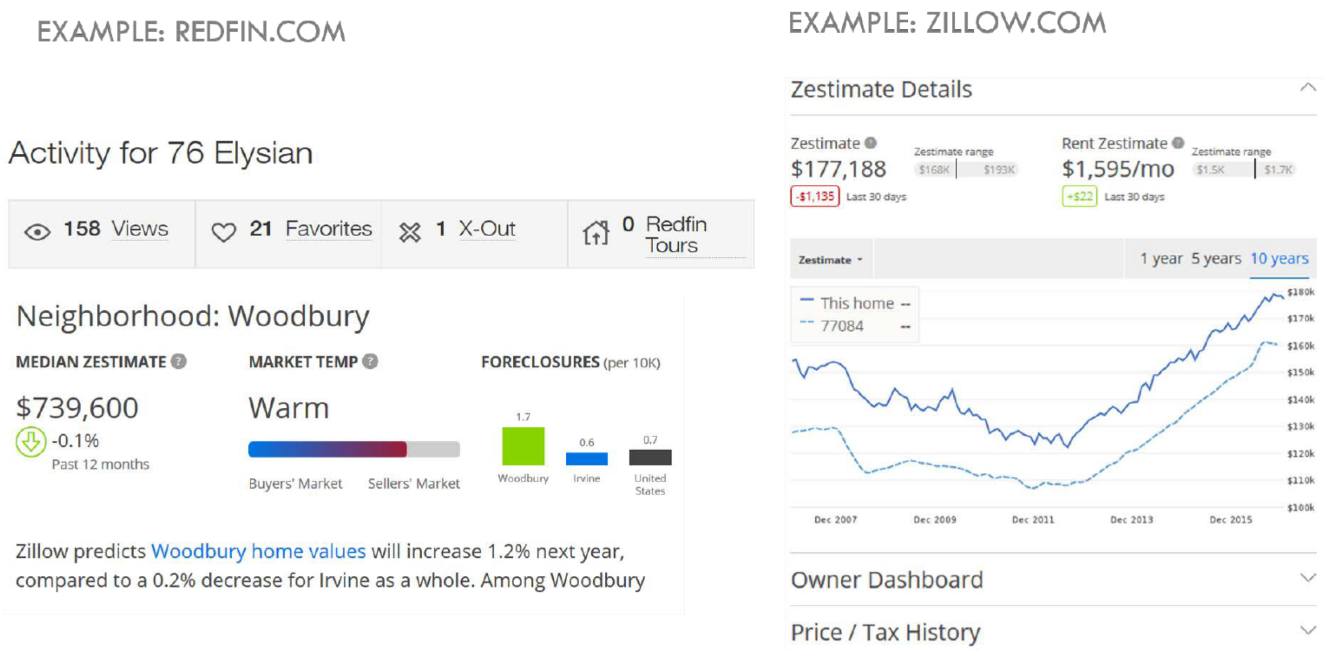
2. LITERATURE REVIEW

The theoretical prediction that when buyers and sellers have asymmetric access to information relevant to the transaction, the party with more information is likely to have an upper hand, can be traced back to the literature in bargaining (for a summary, see Raiffa, 1985). Related to the idea of differential access and processing of information, the seminal work on signaling (Spence, 1973) that spawned a new branch of economics called of information economics. While prospective homebuyers' search for information online is not new, academic research on the topic is just beginning to emerge where some experimental data was used (e.g., Loveland et al., 2014). An extensive literature search at even broader level of online information and selling price resulted in only a couple of scholarly publications. Morton et al. (2011) found from the car shopping study that customers who knew the invoice price paid lower price (pp.395).

As newer and newer technologies are introduced, access to information gets more convenient. Before the Internet era, print media and some closely held computerized media and personal relationships such as salespeople, friends and family, were the sources of information. In this sense, this study is a subset of the all the technologies currently in use affecting dissemination and utilization of information. Customers and sellers alike use websites, a myriad of social media outlets such as Facebook, Instagram, and Twitter, in order to promote and observe behavior of the crowd. On the consumers' side, use of technology provides other nonfinancial benefits such as reducing search time, access to wider number of choices, and prepare for financing the purchase (Zumpano, Johnson, and Anderson (2003). Vijayakumar et al. (2021) focuses on how characteristics of online reviews themselves, like star rating, length, and helpfulness votes, can impact consumer behavior. The way reviews are presented can influence how easily consumers can switch between online stores. In this paper, we focus on information sharing sites such as Zillow.com, and Redfin.com.

When the idea of information asymmetry is discussed, modern technology gave rise to classifications of information collected and shared by various parties. For instance, popular keywords searches can be collected from search engines like Google and the trend and frequency of certain keywords can reveal rich information that can be used to predict demand, voting behavior, traffic patterns, and other crowd behavior of interest. In the context of real estate, surge in online search activity can predict impending purchase intention and resulting price increase. In a study of real estate related searches, it is found that metro areas with higher than normal search activity for house to buy resulted in as high as 8.5% price increase in home prices over a two year period (Beracha and Wintoki, 2013). Das, Ziobrowski, & Coulson (2015) found evidence for the impact of keyword searches in search engines on real estate equity prices, once controlled for other relevant factors. Coulson (2015) found that apartment related online search activities are contemporaneously related to reduced vacancy rates of apartments for rent. What is more significant in his study is that the search intensity translated into real estate investment trust (REIT) stocks, as apparently REIT investors incorporate online search statistics in their investment decisions.

Figure 1: Examples of Information Sharing in Two Major Portals: Redfin.com and Zillow.com



It is reported that real estate investment trust (REIT) portfolio managers actively monitor the search trends in apartment rental related searches in online search engines in order to predict movements in REIT stocks. Braun (2016) studied the investor sentiment using Google internet search data and its impact on volatility forecasts of U.S. REIT market. However, these two studies excluded social media like information sharing by buyers, sellers, and real estate agents. For instance, on Redfin.com, real estate agents can leave remarks on the house after having toured the house in question. Video technologies such as 360 degree views of the interior of the properties and aerial photography of the property and surroundings are increasingly becoming common features of real estate listings on the Internet. Interactive features such as simulation of properties with desired furniture placed in various places in the interior of the property is also becoming added on features of listings. Prospective buyers who browse also post ratings of real estate listings as well as features of the properties based on the technologies used. Other geo-spatial features such as walking ability, access to transportation, amenities, school district are also shared online. In this study, these characteristics are not included in the analyses due to spotty availability of data.

3. THEORETICAL FOUNDATION

Technology Acceptance Model (TAM)

Developed by Davis (1989), TAM proposes that perceived usefulness and perceived ease of use are the primary determinants of a user's intention to adopt and utilize a technology (Davis, 1989). In the context of online reviews, perceived usefulness translates to the extent to which users believe reviews will help them make informed decisions. This is influenced by factors like the perceived credibility and comprehensiveness of the reviews. Credibility hinges on the reviewer's perceived expertise and potential biases, as highlighted by McCafferty (2016). Reviews from seemingly knowledgeable individuals with a neutral stance are generally considered more credible. Additionally, comprehensiveness refers to the level of detail and variety of perspectives offered in the reviews. A review that provides in-depth analysis and covers multiple aspects of a product or service is perceived as more useful than a brief, one-dimensional comment (Verhoef et al. (2003)). Perceived ease of use, on the other hand, relates to the user's perception of how effortless it is to find, read, and understand online reviews. This is impacted by the design and functionality of the review platform. A user-friendly interface with clear navigation, search filters, and easy-to-understand rating systems will enhance perceived ease of use and encourage users to engage with reviews, as confirmed by Yoon (2009).

Venkatesh et al. (2000) further extended the TAM theory by incorporating additional factors like social influence and cognitive instrumental processes. This demonstrates a more comprehensive understanding of TAM beyond its core constructs. Social influence, as introduced by Venkatesh and Davis (2000), can be particularly relevant in the context of online reviews. For instance, positive reviews from friends or trusted online communities can significantly influence a user's decision to rely on reviews. The TAM suggests that the adoption of technology will be driven by psychological constructs such as perceived usefulness and perceived ease of use—both superimposed by other factors such as social influence, individual differences, and facilitating conditions. It is not surprising that TAM is one of the theoretical motivations for homebuyers' use of online applications.

Information Asymmetry

Information economics suggests that when buyers and sellers have uneven access to information, the party with less or lower quality information loses out in a transaction ((Stiglitz, 2008, 1985; Spence, 1973)). Further, both buyers and sellers often deliberately share information in order to get an advantage in the transaction. For example, a seller might boast A+ rating from Better Business Bureau to trumpet business leads. Further, reviews and ratings left by consumers on ecommerce and information sharing platforms inform prospective consumers' consideration or purchase decisions.

While prospective home buyers' search for information online is not new, academic research on the topic is just beginning to emerge (e.g., Loveland et al., 2014). An extensive literature search at even a broader level of online information and selling price resulted in only a couple of scholarly publications. Morton et al. (2011) found from a car shopping study that customers who knew the invoice price ended up paying lower price (pp.395). Sangwon Park, and Juan Nicolau (2007) examines how online reviews can have varying effects on consumers. It suggests that people find both very positive and very negative reviews more useful than lukewarm ones, with negative reviews being perceived as even more informative. Valuable insights like these can be generated for real estate transactions as well, as posited in the following hypothesis:

H_0: Numbers of views and favorites have no significant effect on home selling prices, other things being equal.

H_A: Numbers of views and favorites have a significant effect on home selling prices, other things being equal.

A positive effect would imply more seller empowerment, while a negative one should point to relative information advantage to the buyers, other things being equal.

4. DATA AND METHODOLOGY

To test the hypothesis, we used data from popular real estate websites Zillow.com and Redfin.com. We randomly selected 200 single-family homes sold in Orange County, California, in January 2020. We collected the hedonic properties (characteristics that influence the value) of these homes from Redfin.com. Additionally, we manually copied the view count and number of times each property was saved as a favorite on Zillow.com. Due to the manual data collection process, expanding the sample size to other regions was not feasible. However, a sample size of 200 is sufficient for reliable estimation of a regression model with seven explanatory variables. Multiple regression is a widely accepted method in related literature to test such hypotheses. The following regression model is posited:

$$
\begin{aligned}
&Sold\_price = \beta_0 + \beta_1 Number\_of\_listing\_views + \beta_2 Number\_of\_Favorites \\
&+ \beta_3 Days\_on\_Market + \beta_4 \mathrm{Pr}ice\_reduction + \beta_5 Seller\_equity + \beta_6 SQFT \\
&+ \beta_7 Bathrooms + \beta_8 Bedrooms + \varepsilon
\end{aligned}
$$

Where the first two independent variables pertain to hypothesis $H_{1,}$ and other variables are control variables. The βs are coefficients to be estimated and ε is a white noise error term to facilitate estimation.

It should be noted that Hypothesis H_0 may merely point to an existence, or not, of any effect on price. Setting up experiments to study causal relationship is extremely difficult in real estate settings. Furthermore, collecting primary data using surveys may entail bias of self-reported information. Given this backdrop, using secondary data provides an important opportunity to derive preliminary findings to test the hypothesis proposed above.

5. RESULTS

Before getting ready to estimate the models, descriptive statistical analyses were performed to understand the data set better and detect any unusual characteristics of the variables. Table 1 provides descriptive statistics of the variables included in the model above. As can be seen, the data set does not show any outliers and the central tendencies look reasonable based on recent home prices in the area.

Table 1 Descriptive Statistics (sample size=200)

Variable	Label	Mean	Std Dev	Minimum	Maximum
Sold_Price	Sold price	697,840	422,216	365,000	2,400,000
Days_on_market	Number of days the property has been on the market (DOM)	121	99	16	387
Days_on_market_sq	DOM squared	24,072	39,850	256	149,769
Views_per_DOM	Number of views per DOM	14	23	0	85
Favs_per_DOM	Number of people saved as "favorite" in the portal	0	1	0	3
Reduction	Amount of price reduction	17,848	31,315	0	105,000

Sqft	Living area in square feet	1,713	523	1,099	3,124
Beds	Number of bedrooms	3	1	2	4
Baths	Number of bathrooms	2.12	0.60	1.0	3.5
Equity	Equity-previous purchase price subtracted from current price	267,014	296,907	(55,493)	1,090,588

Table 2 provides Pearson's correlation coefficients for the variables included in the analyses and the matrix does not reveal any counter-intuitive relationships between variables. The numbers in italics represent p-values for the null hypothesis that the pertinent correlation coefficient is zero. It is interesting to note that *Views_per_DOM* is positively correlated with *Favs_per_DOM*, with a moderate correlation coefficient. This suggests that it is easier for a potential buyer to view a property but saving it as a favorite means the property must have better resonated with preferences of the browser.

Table 2 Pearson's Correlation Matrix of the Included Variables

		1	2	3	4	5	6	7	8	9
1	Sold_Price	1.00	0.63	-0.20	-0.17	-0.13	0.79	0.23	0.71	0.47
			0.00	*0.33*	*0.41*	*0.52*	*<.0001*	*0.25*	*<.0001*	*0.03*
2	Days_on_market	0.63	1.00	-0.31	-0.49	0.43	0.45	0.21	0.36	0.27
		0.00		*0.14*	*0.01*	*0.03*	*0.03*	*0.32*	*0.08*	*0.24*
3	Views_per_DOM	-0.20	-0.31	1.00	0.46	-0.24	-0.33	-0.49	-0.23	-0.28
		0.33	*0.14*		*0.02*	*0.24*	*0.10*	*0.01*	*0.25*	*0.22*
4	Favs_per_DOM	-0.17	-0.49	0.46	1.00	-0.27	-0.18	-0.32	-0.23	-0.23
		0.41	*0.01*	*0.02*		*0.19*	*0.37*	*0.11*	*0.25*	*0.31*
5	Reduction	-0.13	0.43	-0.24	-0.27	1.00	-0.06	-0.04	-0.20	-0.06
		0.52	*0.03*	*0.24*	*0.19*		*0.75*	*0.84*	*0.32*	*0.81*
6	Sqft	0.79	0.45	-0.33	-0.18	-0.06	1.00	0.31	0.77	0.72
		<.0001	*0.03*	*0.10*	*0.37*	*0.75*		*0.12*	*<.0001*	*0.00*
7	Beds	0.23	0.21	-0.49	-0.32	-0.04	0.31	1.00	0.19	0.33
		0.25	*0.32*	*0.01*	*0.11*	*0.84*	*0.12*		*0.37*	*0.15*
8	Baths	0.71	0.36	-0.23	-0.23	-0.20	0.77	0.19	1.00	0.56
		<.0001	*0.08*	*0.25*	*0.25*	*0.32*	*<.0001*	*0.37*		*0.01*
9	Equity	0.47	0.27	-0.28	-0.23	-0.06	0.72	0.33	0.56	1.00
		0.03	*0.24*	*0.22*	*0.31*	*0.81*	*0.00*	*0.15*	*0.01*	

An ordinary least square (OLS) model is estimated using a expanded data set of 200 transactions, in order to test the hypothesis H_1. The results obtained, as presented in Table 2, suggest evidence for significant impact on prices arising from information sharing. The model fit is excellent as shown by the F-statistic being significant at 1%, and an adjusted R-square of 0.84 which implies that 84% of the variation in dependent variable is explained by the regression model after adjusting for degrees of freedom. As per coefficients of individual independent variables, results show a positive significant effect of number of favorites—pointing to sellers' advantage. Since the coefficients reported are standardized, one can see that DOM is the most influential predictor and it is statistically highly significant. The finding that Views per DOM is the weakest of the predictors and not being significant is consistent with our expectation that mere view count should not hold much information for predictive purposes. However, the sign of the coefficient is positive, implying that more view count would result in higher sold price (but based on this sample, this effect is not statistically significant). The third most influential predictor is Favs per DOM, having a positive and statistically significant impact on sold prices and implying that is a house is saved by more and more people that is a reliable indicator of how high the price of the property will go in the final sale. Price Reduction is showing a negative and significant impact on the sold price, suggesting that once price has been revised downwards, buyers perceive a negative connotation with this change which perhaps leads to lower offer prices and eventual lower sold price. The variable Number of Bedrooms is statistically significant at 5% level, while the number of bathrooms is not statistically significant. The VIF for this variable being greater than 2.5 is an indication that it could be highly multicollinear with another explanatory variable, namely Size of the house (recall that the correlation coefficient between these two variables is .77, meaning a larger house is likely to have more bathrooms, more so than the number of bedrooms). Expanding the sample size could alleviate the problem of multicollinearity as could running a ridge regression, however this is left for future research. It is interesting to note that having equity in the house leads to lower sold price, which runs counter to the operation of an efficient market. In a perfectly competitive market, the information about seller's equity in the house should be immaterial because market forces will lead to the same or similar price of comparable properties regardless of seller's equity position. However, one explanation for this finding may be that homeowners (sellers) with higher equity may be prone to accept lower offer price because they have more margin to work with, compared to a seller who has less equity (assuming the debt or other obligations of sellers remaining the same).

Table 3: Ordinary Least Square Results (Dependent Variable = Sold Price)

Independent Variables	Standardized Coefficient[a]	t-ratio	VIF
Intercept	0	-3.07	0
	(0.034)		
Days on the market (DOM)	0.634***	4.02	2.14
	(0.000)		
Views per DOM	0.015	0.31	1.89
	(0.764)		
Favs per DOM	0.287**	2.13	2.07
	(0.044)		
Price reduction (in dollars)	-0.262**	-3.42	1.60
	(0.049)		
Size of the house (square foot of living area)	0.566***	2.73	1.89
	(0.002)		
Number of bedrooms	0.195**	2.73	2.08
	(0.002)		
Number of bathrooms	0.342	1.60	3.23

	(0.127)		
Equity (listing price minus prior purchase price)	-0.185**	-2.35	2.08
	(0.037)		
R^2	0.89		
Adjusted R^2	0.84		
F	14.30***		
No. of observations	200[a]		

[a] Standardization puts predictor variables into one scale, facilitating comparison of main effects.

[b] Each unit of observation represents one individual real estate transaction.

*** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level. P-values are provided in parentheses underneath coefficient estimates.

It is noteworthy that most of the variables are statistically significant, and they exhibit the expected direction of relationship. P-values are shown in parentheses under respective coefficients. The variance inflation factor (VIF) suggests only bathrooms are moderately multicollinear (perhaps with bedrooms). Some researchers recommend considering VIF values above 2.5 as indicating considerable collinearity (Johnston *et al.* (2018). Based on this criterion, a new model is run after excluding number of bathrooms (VIF 3.23) and the model still shows the key variables statistically significant. To test the normality of regression residual, normality tests are done, and it shows that the null hypothesis of residual being normally distributed cannot be rejected.

Table 4: Test of Normality of Regression Residuals

Tests for Normality				
Test	**Statistic**		**P Value**	
Shapiro-Wilk	W	0.953	Pr < W	0.424
Kolmogorov-Smirnov	D	0.135	Pr < D	>0.150
Cramer-von Mises	W-Sq	0.068	Pr > W-Sq	>0.250
Anderson-Darling	A-Sq	0.387	Pr > A-Sq	>0.250

Table 5: Ordinary Least Square Results (Dependent Variable = Sold Price) After Dropping a Highly Multicollinear Variable.

Independent Variables	**Standardized Coefficient[a]**	**t-ratio**	**VIF**
Intercept	0	-2.50	0
Days on the market (DOM)	0.752** (0.027)	5.42	2.15
Views per DOM	0.040 (0.764)	0.31	1.89
Favs per DOM	0.306** (0.045)	2.24	2.09
Price reduction (in dollars)	-0.262** (0.049)	-2.19	1.61
Size of the house (square foot of living area)	0.567*** (0.002)	3.86	2.42

Number of bedrooms	0.248 (0.109)	1.73	2.30
Equity (listing price minus prior purchase price)	-0.321** (0.037)	-2.35	2.08
R^2	0.89		
Adjusted R^2	0.83		
F	14.30***		
No. of observations	200[a]		

[a] Standardization puts predictor variables into one scale, facilitating comparison of main effects.

[b] Each unit of observation represents one individual real estate transaction.

*** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level

Working with more data could alleviate the multicollinearity. Data also should be cleaned to get rid of "self-rated favorites," or frivolous favorite marks, with the help of the vendor or the real estate portal.

6. CONCLUSION

This paper posited that online information sharing by buyers, sellers, and real estate agents have meaningful effect on the final selling prices of a house. An empirical investigation of this hypothesis is conducted using a randomly chosen sample of 200 residential real estate listings from the popular real estate portal Redfin.com was used to test the research question whether such online information sharing in the form of saved "favorites" by users and number of views have statistically significant effect on sold prices. Econometric results obtained in this investigation suggests this effect is statistically significant even when other variables such as house characteristics are controlled for. Controlling factors included in the model also reveal interesting additional findings. For instance, days on the market appears to be a significant and positive predictor of home prices. This finding might appear counter intuitive because if a property sits on the market longer, the prospective buyers might suspect unseen problems with the unit. On the other hand, sellers who can be patient until a suitable buyer come along might benefit from a higher selling price. Perhaps the latter explanation is proving true, based on the results in this study. Furthermore, the number of views registered by a property is not statistically significant, while the implied effect is positive. This is also plausible because there may be more interest in looking at the property for a variety of reasons not pertaining to an intention to make an offer on the property. Some people just like to look at houses for sale in order to get ready to sell their own or to keep abreast of the real estate trends.

Findings from this study provides evidence in support of the hypotheses put forward for testing in this proposed research. The second hypothesis pertains to empowerment of buyers and sellers due to wider availability and use of information about prospective buyers' preference and other users' reviews of real estate listings. This hypothesis will be tested using survey data of registered users of major real estate portals. Future extensions of this study include understanding the effect on the speed of transaction closing of online information sharing and keyword searches in online search engines.

7. LIMITATIONS AND DIRECTIONS FOR FUTURE RESEARCH

While this paper provides interesting and new findings about online search activities and residential real estate prices, there are some shortcomings due to the nature of data used in the analyses and the type of research methods used. It is difficult to clean up the potential contamination of data in recording of views because it is unclear what percentage of "viewers" are serious buyers or whether they are even from the geographic area in question. Only cooperation from the real estate portals can help alleviate this problem. The number of favorites recorded in the listing can be subject to manipulation if a seller intended to inflate the number by rating from friends and family. These frivolous favorite marks can be identified with the help of the vendor or the real estate portal. The research methodology used in this study is an econometric study, which invariably uses secondary data, and the researcher has little or no control over how the data is collected. A potential extension of this study would be to include experimental methods, using research participants. For instance, if responses are collected from groups of randomly selected participants after showing them fictitious listings with various levels of views and favorites, the resulting difference in response might provide results deriving from a more controlled environment. Future research in these avenues should enrich the findings presented in this paper.

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