Information and Real Estate Transactions: The Effects of Pictures and Virtual Tours on Home Sales*

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Abstract

Visual information displayed in residential real estate listings, such as pictures and virtual tours, may facilitate the search and matching process between home buyers and sellers. In this research, we use real estate transaction data to a) explore why some sellers provide more visual information on their listings than others and b) assess its effects on a unit's transaction price and time on the market. Using instrumental variables, we find that visual contents have a large and positive effect on marketing outcomes. For instance, adding a virtual tour may increase the expected transaction price by about 2 percent and decrease the expected time on the market by about 20 percent.

Keywords: Real Estate Market, Internet, Pictures and Virtual Tours, Search Models

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1 Introduction

The sale of a heterogeneous durable good, such as a housing unit, involves a costly search process for both buyers and sellers. Buyers look for properties among units for sale, while sellers wait for offers. Because units and buyers' tastes are heterogeneous, the search process usually takes time and effort.

The real estate industry has developed information systems, such as Multiple Listing Services (MLS), that facilitate matching between buyers and sellers. Most MLS listings are available to the public on the internet, allowing potential buyers to search among for-sale units at a low cost.[1] More importantly, the internet provides opportunities to display large amounts of visual information on the listing that may be relevant to potential buyers. In particular, online real estate listings may be enhanced with pictures and virtual tours which, typically, ease the buyer's task of identifying a subset of properties for a personal visit.

Recent studies have analyzed the impact of internet use on the efficacy of buyer's search (D'urso 2002 and Zumpano et al. 2003) and the seller's marketing outcomes (Ford, Rutherford, and Yavas 2005).[2] Less is known, however, about the effects of displaying additional information in online listings on real estate transactions. The availability of pictures and virtual tours in real estate online listings provides an opportunity to test these effects in a direct fashion because a) the quantity of information provided about the unit is readily observed and easily quantified and b) there is substantial variation in the number of pictures

[1] In most areas in the US, MLS listings are also available on the internet. Thus, potential buyers can view them even if they have not hired a real estate agent.

[2] In a related study, Hendel, Nevo, and Ortalo-Magné (2007) compare transaction outcomes obtained by sellers who listed their home on a newly developed web site versus those who used traditional agents and the Multiple Listing Service.

and virtual tours displayed in online listings.[3]

In this research, we use individual home transaction data to measure these effects. In particular, we a) explore why some sellers provide more visual information on their listings than others and b) assess the effects of pictures and virtual tours on a unit's transaction price and time on the market.

Economic theory provides several insights about the sellers' incentives to display visual information on their listings. For example, if pictures and virtual tours reveal the true quality of a home, sellers with lower disclosing costs may have higher incentives to post this information (Grossman 1981, Milgrom 1981, and Jovanovic 1982). The theory also suggests that, if visual information decreases buyers' search costs, the value of the buyer-seller match may be higher for those units that provide more information. Thus, there may be a positive correlation between the amount of visual information in the listing, the quality of the unit, and the sale price.[4] These theories guide the specification of our empirical models.

To achieve our empirical goals, we gathered data from several sources. First, we collected information on all completed residential real estate transactions in Fairfax County, VA, listed on the MLS between January 2006 and June 2007. The transaction data were matched with Fairfax County Assesor's and with Census data to compile information about each unit's transaction price, number of days on the market, availability of pictures and virtual tours in the listing, and detailed property and neighborhood characteristics.

We first identify the determinants of pictures and virtual tours on housing listings using

[3]For example, in the listings used in this study (which correspond to a sample of residential listings from the Washington D.C. Metropolitan Area from December 2006 to June 2007), 75 percent had a virtual tour available and the number of pictures displayed ranged from zero to 27 with an average of 7.5 pictures per listing. Details are found in the data section.

[4]We discuss these points in the next section.

a linear and a probit model, respectively. As the theory predicts, our results evidence a negative correlation between the visual contents of a listing and certain characteristics of the unit and the seller that, we argue, are appropriate measures of the seller's disclosing costs.

To measure the effects of pictures and virtual tours on prices and time on the market, we then use linear regression models. The explanatory variables include the availability of pictures and virtual tours as well as the home's characteristics. We first use ordinary least squares (OLS) to describe the underlying correlations and, as expected, find a positive correlation between home prices and the amount of visual information provided on the listing. Second, to measure casual effects, we use instrumental variables and two stage least squares (TSLS). Instrumental variables are needed to identify any causal effect since posting pictures and virtual tours are sellers' choice and, thus, may be endogenous.

The TSLS estimates suggest that pictures and virtual tours have a surprisingly large (and statistically significant) positive effect on the expected sale price of a home. For instance, adding a virtual tour may increase the expected transaction price by about two percent, and ten additional pictures may increase the home's sale price by 1.7 percent. Furthermore, pictures and virtual tours may speed up the marketing time. For example, the availability of a virtual tour may decrease the expected time on the market by about 20 percent.

The rest of the paper is organized as follows. Section two describes related studies. In Section three we briefly discuss our empirical methods. Section four provides a description of the data. Empirical results are analyzed in section five. The last section concludes.

2 Theories and testable implications

Information disclosure

Home sellers have the option to include visual information on their listings. This information may be relevant for potential buyers, who can use it to gain additional knowlege about the quality of the housing unit. Thus, by selecting the number of pictures that are displayed on the listing, sellers may be implicitly selecting an optimal level of disclosed information about their products' quality.

The "unraveling" predictions in Grossman (1981), Milgrom (1981), and Jovanovic (1982) suggest that, as long as disclosure costs are small, sellers have strong incentives to voluntarily disclose information about the true quality of their product. Grossman (1981) and Milgrom (1981) show that a monopolist that faces no disclosure cost will reveal the quality of its product and Jovanovic (1982) extends this results for a market with a large number of firms. The "unraveling" prediction is quite intuitive. Buyers will assume that non-disclosing sellers (for example, listings with few or no pictures) have lower quality units than those that disclose; thus, high quality non-disclosing sellers will have an incentive to reveal their features (adding more pictures) to differentiate from the other non-disclosers in order to attract potential buyers. Jovanovic (1982) also shows that if disclosure costs are positive, the optimal disclosure policy is characterized by a quality threshold: if the quality is below this threshold, the seller would not disclose and vice versa.

If the unraveling predictions are true, one may expect to observe a positive correlation between the quality of the unit and the number of pictures on the listing. Lewis (2007) provides such evidence for the market of used cars in eBay. His findings suggest that sellers use a selective disclosure policy, where owners of high quality cars voluntarily provide more information (more text and pictures) than their low quality counterparts.

The unraveling theory provides us with a couple testable implications. First, as disclosure costs increase, we would expect to see lower levels of information on the listing. Second, all other things equal, properties with a higher number of pictures and virtual tours may be of higher quality and, thus, sell for more. That is, there may be a positive correlation between the number of pictures and the sale price.

Information and matching

The search and matching process between home buyers and sellers can be costly.[5] Buyers incur expensive visiting and inspection costs, while sellers bear both the expense of keeping their homes on the market and the cost of showing them to potential buyers. As Ford, Rutherford, and Yavas (2005) point out, the use of online listings may decrease buyers' search costs (relative to "off-line" listings), allowing them to search more intensively and find a better match. Similarly, enhanced visual information in online listings should allow potential buyers to make a better selection of properties that would be considered for a personal visit/inspection. If the availability of pictures and virtual tours on listings allows buyers to pick a "better" set of homes to visit, the expected value of the buyer-home match should increase. As long as the surplus from trade is shared between buyers and sellers, better matches should generate higher sale prices.

Recent studies also suggest that there may be a positive correlation between listings that provide visual information and the quality of the buyer-seller match (the surplus from trade). For instance, Burdett and Coles (1997), Eeckout (1999), Schimmer and Smith (2000), Smith (2002), and Adachi (2003) have explored the role played by search frictions in matching

[5] To account for these search costs, authors have often used search models to explain the behavior of buyers and sellers in the housing market. The earliest application of a search model in a formal analysis of real estate markets is attributed to Yinger (1981). Later developments can be found in Yavas (1992), Horowitz (1992), Yavas and Yang (1995), Haurin (1998), Arnold (1999), Ford, Rutherford, and Yavas (2005), Albrecht et al. (2007), and Carrillo (2007), among others.

models. A common feature of these models is that, as search frictions decrease, the quality of the buyer-seller match generally increases. If visual information decreases search frictions, then the average match quality of those listings that provide more information should be higher.

The previous discussion also provides some insights about the type of sellers who may benefit the most from visual information. For instance, if buyers have high matching costs and heterogeneous tastes for the characteristics of housing units, homes with a general appeal may find better matches than units with a specialized appeal (Sundaram 2000). This situation reverses as the search frictions decrease.[6] Thus, owners of "unique" properties may have a greater incentive to include visual information on the listing.

Testable implications

We are concerned with two questions: a) are there any systematic differences between those listings that display pictures and virtual tours with respect to those that do not and b) are there any effects of using visual information on marketing outcomes?

The theory suggests that variation in visual information in online listings could be explained by differences in the seller's disclosure costs, as well as by differences in the unit's quality and degree of heterogeneity. In particular, sellers with high disclosure costs should be less likely to include pictures and virtual tours on their listings. In addition, one would expect that higher quality and more heterogeneous homes will be more likely to provide visual information.

[6] This result is quite intuitive. If search frictions are high, the buyers' outside option (their value of continuing searching) is relatively low, and they become less selective. Less selective buyers accept (buy) average units more often. Units with specialized appeal receive fewer offers even though they are still appealing for a set of buyers (even for those who settled with an average home). As search costs decrease, buyers become more selective, search more intensively, and the units with special appeal attract the best matches.

The theoretical models discussed above suggest several correlation patterns in home sales data. For instance, a selective information disclosure policy may induce a positive correlation between home prices and the amount of visual information on the listing. In addition, the positive correlation between prices and visual information may be even higher since pictures and virtual tours allow buyers to find better matches.

It is not clear, however, if there should be any particular correlation between the visual contents on a listing and the time that a property stays on the market. On one hand, the theory suggests that higher quality units are more likely to display visual information. In addition, buyers may realize the benefits from browsing listings with visual information and may pay little attention to listings without it. Thus, a listing with many pictures and a virtual tour may be more appealing to buyers, have a higher "viewing" rate and, ceteris paribus, sell faster. On the other hand, "unique" properties should be more likely to display more visual information and also, on average, should take a longer time to find an interested buyer. These opposing effects make it difficult to predict a-priori any correlation between these variables.

The correlations in the data provide vaulable insights and allow us to validate the predictions from the theory. They do not identify, hiwever, the causal effects of visual information on marketing outcomes. To identify these effects, ideally, one could design an experiment where pictures and virtual tours on listings are randomly assigned and, later, marketing outcomes between the "treated" and the "control" groups are compared. Unfortunately, we do not observe such an experiment. As a viable alternative, we use instrumental variables to identify these effects.

3 Empirical models

We have two empirical goals. First, we search for systematic differences between those listings that provide more information with respect to those that do not. Second, we assess the effects of posting more information on a unit's transaction price and time on the market. Let y be an appropriate measure of the amount of information contained on a listing.

To explain the variability of the information displayed on real estate listings we use a linear model

$$y_i = X_i\beta + Z_i\gamma + e_i, \tag{1}$$

where Z is a set of the unit's characteristics, the vector X includes variables that affect the seller's relative costs of displaying information on a listing, β and γ are vectors of parameters, and e is an unobserved error term. The unit's characteristics provide a measure of its quality. Thus, the parameter γ describes the relationship between disclosed information and the (observed) quality of the good. On the other hand, the parameter β provides an estimate of the relationship between the costs of displaying information (disclosing costs) and the contents of a listing.

Measuring the amount of information on a product's listing is, generally, not straightforward. However, the amount of information displayed on real estate online listings can be easily and objectively measured by the number of pictures it contains and by the presence of virtual tours. With these two measures on hand, we may estimate two versions of equation (1). The first one is a linear model where the dependent variable is the number of pictures on a listing. In the second version, we use a probit model to explain the availability of virtual tours.

To identify the effects of posting more information on a unit's transaction price and time on the market we use two separate hedonic models. The dependent variables in each model are the log of the transaction price and time on the market, respectively. Besides the characteristics of the unit, the independent variables include the number of pictures and the availability of a virtual tour on the listing. If the hedonic models are estimated using ordinary least squares (OLS), the coefficients on the listing variables measure correlations between pictures and virtual tours and marketing outcomes. If instrumental variables are used, these coefficients may identify causal effects. We discuss these points at further detail later.

4 Data and definition of variables

The data includes all completed residential real estate transactions in Fairfax County, VA, that were listed between January 2006 and June 2007. Fairfax County is located in Northern Virginia and is part of the Washington, DC, metropolitan area.

The MLS data have information about units' transaction prices, number of days on the market, and detailed property and listing characteristics. The property characteristics include several details about the features of the home, such as the number of bedrooms, bathrooms, age, vacancy status, and location (individual address). In addition, we observe certain features of the listings, such as the number of pictures that were displayed and the availability of virtual tours.

The MLS data is complemented with information from other sources. For instance, using individual addresses, we match the MLS records with Fairfax County's assessor database. The assessor database contains a complete set of the unit's characteristics that were not always available in the MLS listings. Using this matching, we can use MLS listings that were missing information on key variables.[7] In addition, we were able to match most of our records with US Census data at the Block-Group level and include several Census variables that explain neighborhood desirability.

Table 1 shows a list of the relevant variables. The sale price and the time that the unit was on the market provide information about the transaction. The number of pictures that were posted on the listing as well as the availability of a virtual tour provide information about the amount of information displayed on the listing.

[Please, insert Table 1]

As described in the previous section, we aim to compute variables that depict the seller's relative costs of displaying pictures and virtual tours in online listings. Ideally, we would like to observe an objective measure of these disclosing costs or to have access to sellers' demographic characteristics to estimate them. Since we do not have this information, we approximate sellers' listings costs using estimates of the accessibility to the required technology and the vacancy status of the units.

Our measures of accessibility to technology include the average number of pictures and average number of virtual tours that other agents within the same broker firm use.[8] Due to peer-efects, a seller and her agent may be influenced by the average number of pictures

[7] For example, a large percentage of our MLS data lacked information on square footage. By using the assessors database, we were able to obtain this information and use this variable in our models.

[8] For example, let p_{ij} be the number of pictures available on listing i which is sponsored by agent j. Furthermore, let n_j be the number of listings posted by agent j and N the total number of listings on the broker firm. For each listing, we compute the variable zp as follows

$$zp_{ij} = \frac{1}{N - n_j} \sum_{k \neq j} \sum_{i} p_{ik}.$$

and virtual tours displayed by other agents in the firm when choosing the contents of her own listing. More importantly, the sunk costs of learning and adopting this technology may decrease as the share of users increase. Thus, a positive coefficient on these variables may confirm the predictions of the theory.

The vacancy status of a unit may also be a good indicator of the costs that a seller must incur in order to post pictures and virtual tours. This variable equals one if the unit is vacant and zero otherwise. We hypothesize that the costs of taking pictures are higher if the seller does not live in the unit.[9] Thus, a negative coefficient on this variable may be consistent with the theoretical models discussed in the previous section.

The seller's motives to sell a property may also determine her (relative) disclosure costs. For this reason, we consider two variables that capture the seller's incentives to trade her home. First, as in Knight (2002) and Glower and Haurin and Hendershott (1998), we compute a markup index that estimates the percent difference between the original listing price and the home's value (at the time of the original listing). The original listing price is obtained from MLS data. Additionally, in order to obtain an estimate of the home's value, additional hedonic regressions are performed.[10] Overpricing or under-pricing real estate properties may be the result of sellers' random errors or of strategic behavior. If a fraction of sellers choose this markup strategically, it may be interesting to identify if there are any complementarities between their behavior and the decision of listing pictures and virtual tours.

Second, it is also plausible to assume that more motivated sellers have different incentives

[9] Costs may be higher because some sellers may choose to rent furniture to take "better" pictures of vacant units, for example.

[10] These regressions are not reported in the paper and can be requested from the author.

to sell their property and, thus, may put more effort into selling their homes.[11] To measure seller's motivation, as in Springer (1996), we define a variable that equals one if the seller self-describes as a "motivated seller" in the listing.

The theory suggests that homes of specialized appeal are more likely to display visual information. To test this hypothesis, we follow Haurin (1998) and compute an atypicality index that measures the absolute deviations of a home's observed attributes from typical levels in the area (zip code).[12] In addition, notice that detached units are likely more heterogeneous than multi-family units and, thus, may have a more specialized appeal. For this reason, we also identify if the unit is a "detached residence", a "townhome", or a "condominium".[13]

We also include several variables that describe the physical characteristics of the units and, thus, their quality. The property characteristics include: the unit's square footage, number of bathrooms, number of bedrooms and age, among others. Finally, we compute seven variables from the US Census that may be important for explaining neighborhood desirability. These variables capture the demographic composition of the Census Block Group where the unit is located. They include the population density, proportion of Blacks

[11] For related discussions see Glower, Haurin, and Hendershott (1998) and Albrecht et al. (2007).

[12] Here is a technical definition of the atypicality index. First, we use an auxiliary hedonic regression to obtain the "weights" that will be assigned to each housing feature. Let δ be the vector of estimated weights. Furthermore, define X_{ij} as a vector of home's i attributes located in zipcode j, and $\bar{X}_j = \frac{1}{N_j}\sum_{i=1}^{N_j} X_{ij}$ as the mean home's attributes in the zip code, where N_j is the number of homes sold in each area. Then, for each observation, we construct the atypicality index a as follows

$$a_{ij} = \frac{\left|X_{ij} - \bar{X}_j\right| \cdot \delta}{\bar{X}_j \cdot \delta}.$$

[13] We use the information on the field "type" on the MLS listing to identify if the housing unit is a detached single family home, a townhome, or a condominium. Detached units and townhomes are directly identified from the definitions on the listing. We define that the unit is a "condominium" if the property is part of a low, mid or high building. In the MLS listing, this corresponds to those units whose type is either: "Garden 1-4 Floors", "Mid-Rise 5-8 Floors", or "Hi-Rise 9+ Floors".

and Hispanics and median household income, among others. Our final matched database consists of 15,675 records.

Descriptive statistics are shown in Table 2. The average transaction price was $525,600 with a minimum of $125,000 and a maximum of $1,995,000.[14] In this sample, most homes sold relatively quickly. While the mean time that a home stayed on the market was 50 days, 17 percent of the properties sold in less than one week, and fifty percent sold in less than 33 days. On the other hand, a small number of homes (about 10%) stayed on the market for more than four months.

[Please, insert Table 2]

On average, sellers displayed seven pictures on a listing. There is, however, considerable variation in the number of pictures displayed on ads. For instance, about three percent of listings show no pictures, 33 percent show only one picture, and 20 percent displayed more than 14. Moreover, about 75 percent of sellers included a virtual tour on their listings.

On average, sellers posted a listing price that was four percent higher than the market value of their properties. In addition, three percent of sellers described themselves as "motivated sellers" and about one third of properties were vacant.

A typical home in Fairfax County is about 26 years old, has 1,706 square feet, two bathrooms, and 0.2 acres of land. In addition, an average home in our sample is located in a US Census block-group where 8 percent of its population is black and 8 percent of the population is older than 65.[15] There is significant dispersion in the characteristics of the

[14] To avoid biases in our analysis produced by outliers, we exclude from our database properties that were sold for more than $2,000,000.

[15] Notice, however, that the Census variables' statistics are weighted by the number of homes sold in each Census block-group and do not necessarily represent an accurate description of the whole population of Fairfax County. Instead, they describe only those locations where real estate transactions were made.

neighborhoods. For example, while there are many areas in our sample with virtually no Blacks or Hispanics living in them, there are several Census block-groups that are populated by these groups only.

5 Results

In this section, we first use linear and probit models to explain the observed variabilility of pictures and virtual tours across real estate listings. Then, we assess if pictures and virtual tours have an effect in marketing outcomes.

5.1 Determinants of pictures and virtual tours

We use a linear regression model to explain any systematic differences between the number of pictures that a seller displays and her property's characteristics. The dependent variable is the number of pictures on a listing, and the explanatory variables include the seller's, the unit's and the neighborhood's characteristics mentioned in the previous section. In addition, month-year, and zip code fixed effects have been added to all specifications.

[Please, insert Table 3]

Results are shown in Table 3. The first and second columns report the coefficients and standard errors, respectively. The coefficient on the seller's markup is positive and statistically significant. In particular, a home that displays a posting price 10 percent above the average value of a comparable home with no markup, is expected to display 0.7 more pictures. This result should be interpreted with caution, however. On the one hand, it could be that there are strategic complementarities between pricing and marketing effort. For instance, sellers that overprice their homes may put more effort to market their units by showing more pictures. On the other hand, the positive sign of this coefficient may be subject to an omitted variable bias, since there may be other unobserved features of the home that influence both the over-pricing decision and the contents of the listing.

There is evidence that there are large peer-effects among real estate agents when choosing the contents of their ads. For instance, the expected number of pictures displayed in an agent's listing goes up by one half if the average number of pictures that other agents on the firm display increases by one. In addition, the results on Table 3 suggest that vacant units on average display one less picture than occupied homes. We interpret this as evidence that, as the seller's disclosure costs increase, the information displayed on the listing decrease. These results are consistent with the theoretical predictions.

There are no significant differences in the number of pictures displayed by sellers who describe themselves as "motivated sellers". This finding is not surprising, since self-reported motivation is likely a noisy measure of the true seller's motivation. Thus, the estimate of this coefficient may be subject to attenuation bias.

Results provide no evidence that listings of homes with specialized appeal may show more visual content. On one hand, we do find that detached homes are more likely to display pictures. On the other hand, our estimates suggest that homes that have different attributes than the typical home in the area display fewer pictures. In particular, if the atypicality index raises by one standard deviation, the number of pictures displayed is expected to decrease by about 0.3.

The coefficients on the unit's characteristics provide several insights about the relationship beween the quality of the unit and information disclosure. First, there is evidence that larger homes (with more square footage) are likely to display additional pictures on their listings. Interestingly, once we condition on size, units that have additional bedrooms display fewer pictures. This may suggest that owners dislike showing pictures of small bedrooms. Furthermore, new units display fewer pictures since, most likely, they are not finished when advertised.

Finally, we find evidence that neighborhood conditions have little effect on the amount of pictures displayed on a listing. This is plausible since pictures usually provide information about the unit's features and not about the neighborhood's.

To analyze the determinants of virtual tours we use a binary probit model. The dependent variable is an indicator if a listing displays a virtual tour. The independent variables, as in the previous linear model, include the seller's, the unit's and the neighborhood's characteristics as well as time and location fixed effects.

In the third and fourth columns of Table 3, we show estimated marginal effects evaluated at the means of the explanatory variables and their corresponding standard errors. Overall, it seems that the variables that were significant in explaining the listings' number of pictures have a similar effect on the likelihood of displaying a virtual tour. For instance, higher price markups are positively correlated with the availability of virtual tours. Furthermore, vacant units have a 6 percent lower probability of showing a virtual tour than occupied units. Peer-effects are large and statistically significant. For instance, if the share of other agents who use virtual tours increases by 10 percent, the likelihood of displaying a virtual tour increases by about five percentage points. Larger homes, and homes with additional features (such as fireplaces, and basements) are more likely to include a virtual tour. Finally, we find little evidence that neighborhood characteristics affect the decision to list a virtual tour.

5.2 The effects of pictures and virtual tours

To measure the effects of pictures and virtual tours on prices and time on the market, we use linear models. We start describing the existing correlations between prices, time on the market and the listing characteristics. For this matter, we use ordinary least squares (OLS). Later, to measure causual effects, we use instrumental variables and two stage least squares (TSLS).

Ordinary Least Squares

We consider a log-linear hedonic model where the dependent variable is the natural logarithm of the transaction price and the explanatory variables include characteristics of the listing, the property, and the neighborhood. We explore several specifications and report the coefficients in each column of Table 4.

In our first specification, we let the number of pictures and the availability of a virtual tour be the only explanatory variables. The coefficient on number of pictures is positive and statistically significant. This coefficient, however, may be capturing other size effects, since larger properties generally sell for more and, also, are more likely to display a greater amount of pictures. To control for this omitted variable bias, the second specification includes several characteristics of the unit. As expected, the coefficient on number of pictures decreases once we control for the home's characteristics.[16]

[Please, insert Table 4]

In the third specification, dummy variables for each month-year combination during our sample are included. Since it is likely that the number of pictures and the availability of virtual tours displayed on listings increases over time, the coefficients on these variables may

[16]The coefficients on the unit's characteristics are statistically significant and have the expected signs.

be capturing some of the overall price trends on the market. In particular, residential prices decreased about 9 percent during our sample period, so it is likely the coefficients on the listings variables in the second specification may be biased downwards. As expected, once we control for time effects (third column), both of these parameters notably increase.

The final two specifications introduce other controls that may explain the neighborhood and general area desirability. In particular, we add the Census Block-Group variables and 51 dummies for each of the zip codes in Fairfax County to the hedonic equation. Notice that the coefficient on the number of pictures variable is robust to the inclusion of these controls.

The most complete specification (fifth column) suggests that listings with a large number of pictures and a virtual tour available sell at higher prices. For instance, listings with 10 extra pictures may sell for an additional 1.5 percent and listings with a virtual tour sell on average for 0.8 percent more. As suggested by the theory, even after we control for the unit's characteristics, a positive correlation remains between the visual information on the listing and prices.

To explore the relationship between the time that a property stays on the market and the features of the listing, we estimate several linear models. The dependent variable is the log of time on the market and the independent variables include the unit's and the listing's characteristics. In addition to the explanatory variables used in price hedonic-models, we include the seller's markup and atypicality index.

[Please, insert Table 5]

Parameter estimates are shown on Table 5. The coefficients on the listing's variables are positive, statistically significant, and robust across specifications. The most complete specification suggests that there is a strong positive correlation between marketing time and the availability of virtual tours and pictures. For instance, listings that displayed a virtual tour, on average, stayed about 51 percent more days on the market.

Endogeneity

The listing variables may be endogenous because sellers choose how many pictures to display and whether to add a virtual tour on their ads. For instance, if there are any unobserved components that affect both the listing's characteristics and the dependent variables, it is likely that some of the coefficients on Tables 4 and 5 are biased.

It is easy to argue that the listing variables may be endogenous, but the sign of the bias is not obvious. For example, owners of unusually well maintained homes are likely to display more pictures of their property. It is also the case that unusually well maintained homes face a higher demand and sell, on average, at higher prices. Since maintainance is unobserved (from the econometrician's point of view), the OLS estimates of the listing variables in Table 4 could have an upward bias. However, there may be other unobserved components that introduce a negative bias as well. For instance, it is plausible that highly motivated sellers market their unit more aggressively showing more pictures and virtual tours and, at the same time, are willing to accept higher price discounts.[17]

The biases in the coefficients on the time on the market equation are also hard to predict. On one hand, there is a negative ommitted variable bias since homes with high (unobserved) quality may be more likely to display additional pictures and, also, to sell faster. On the other hand, the longer a home stays on the market, the more opportunities a seller has to enhance his listing with pictures and virtual tours. This introduces a positive simultaneity

[17] Glower, Haurin, and Hendershott (1998) and Springer (1996) show that sellers' motivation affects transaction prices and marketing time.

bias.

For the above reasons, our coefficients of interest on Tables 4 and 5 do not identify the causal effect of the use of pictures and virtual tours on prices and marketing time. Instead, they are capturing the correlation between the listing variables and the transaction outcomes. To identify the causal effects of the use of pictures and virtual tours on the transaction outcomes, we use instrumental variables and TSLS.

Two Stage Least Squares

An ideal instrument should be correlated with the endogenous variable and orthogonal to the unobserved components of the pricing and time on the market equations. With these considerations, we define two sets of instruments. Our first set of instruments is the average number of pictures and average number of virtual tours displayed on the listings of other real estate agents within the same broker firm. Due to peer interaction, we expect that agents who work in offices where listings with many pictures and virtual tours are common are also likely to use them on their own listings. Moreover, we believe that the unobserved features of one particular home-for-sale should not be correlated with the number of pictures that other agents use on their listings.

Our second set of instruments exploits the variation in the distance between the units-for-sale and the broker firms. Our data shows that home sellers generally select brokers that are located at a relative short distance from their homes.[18] Sellers may prefer "local" brokers to save on transportation costs and to take advantage of their specific knowledge about the region's housing market. If this is the case, there may be a positive correlation between, say, the number of pictures describing one particular property and the average number of

[18]The median home-to-broker linear distance is 4.5 miles.

pictures on listings in the nearby area. Moreover, the average number of pictures on listings in the nearby area should be orthogonal to the unobserved features that are specific only to the advertised unit.[19] These unobserved feaures, however, may affect the home's price and time on the market. We define the second set of instruments as a weighted average of the mean number of pictures and virtual tours displayed in listings in broker firms that lie within five miles from each housing unit. To estimate the instruments, we first compute the linear distance between each property and every broker firm that is located within five miles. Then, we calculate a weighted average (weights are a function of the distances) of the mean number of pictures and virtual tours that are displayed on these broker firms.[20]

The instruments are used to compute TSLS estimates of the pricing and time on the market equations and results are shown on Table 6. We find two interesting results. First, there is evidence that pictures and virtual tours have a surprisingly large (and statistically significant) positive effect on the expected sale price of a home. For instance, adding a virtual tour may increase the expected transaction price by about 2 percent (approximately $10,000 in the average unit), and ten additional pictures may increase the home's sale price by 1.7 percent. Our second result suggests that pictures and virtual tours speed up the

[19] Recall that, in our hedonic models, the "observed" features of the property include characteristics of the Census Block Group and zip-code fixed effects.

[20] Let z^p be our first instrument of interest. To compute the weighted average, we use a normal kernel function. That is,

$$z_i^p = \frac{\sum_{j=1}^{J} \phi(D_{ij}) * \bar{y}_j}{\sum_{j=1}^{J} \phi(D_{ij})},$$

where D_{ij} is the linear distance (miles) from property i to the broker office j, $\bar{y}$ is the average number of pictures in the broker firm, J is total number of brokers, and

$$\phi(x) = \left\{ \begin{matrix} 0 & \text{if } x > 5 \\ \exp\{-\frac{1}{2}(\frac{x}{b})^2\} & \text{if } x \leq 5 \end{matrix} \right\}.$$

We let $b = 2.0$ miles (results do change for different choices of b).

To compute our second instrument z^v, we use the same procedure but define $\bar{y}$ as the average number of virtual tours in each broker firm.

marketing time. In particular, we find statistically significant evidence that the availability of a virtual tour decreases the expected time on the market by about 20 percent (or 10 days). The coefficient on number of pictures, though statistically insignificant, is also negative, suggesting that additional pictures increase the probability of selling a home.

Overidentification tests confirm the validity of the instruments. For instance, the p-values of a standard Sargan test are 0.8 and 0.13 for the pricing and time on the market equations, respectively. Thus, we cannot reject the hypothesis that the instruments are orthogonal to the error term (and that the model is correctly specified).

Discussion

If visual information improves the home-seller's marketing outcomes, an obvious question arises. Why does not every seller use these features on their listings? One possible explanation is that listing costs remain large enough to prevent some sellers to post pictures and virtual tours. However, the monetary and non-monetary costs involved in taking pictures and videos of a property, editing them, and uploading these information onto the internet are likely lower than the average $10,000 premium that sellers might obtain from posting a virtual tour. If the choice of posting visual information is made by the real estate agent and not by the owner, however, the premium that the agents may receive from showing a virtual tour decreases to $300 (assuming a 3% commision rate) which, for certain agents, may be below their listing costs.

6 Conclusions

In this paper we have made two contributions. First, we explored why certain listings provide more visual information than others. Second, we used real estate transaction data to assess the effect of visual information on marketing real estate. Our findings suggest that pictures and virtual tours both increase the expected transaction price and decrease the average time on the market of comparable listings. For example, adding a virtual tour decreases the expected marketing time by about 20 percent and increases the expected sales price by about 2 percent.

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Table 1: Description of variables

Variable	Description
	Transaction
Price	Transaction price in thousands $
DOM	Days on the market
	Listing
Virtual	Equals one if listing has a virtual tour and zero otherwise
Number of picture	Number of pictures in listing
	Seller
Markup	Percent difference between original listing price and property's value
Motivated	Equals one if seller describes himself as a "motivated seller" and zero otherwise
Vacant	Equals one if unit is vacant and zero otherwise
Pictures peers	Mean number of pictures used in listings of other agents in the same broker firm
Virtual peers	Mean number of virtual tours used in listings of other agents in the same broker firm
	Housing unit
Atypicality	Atypicality index
Sqft	Living area square feet
Acreage	Lot acreage
Bedrooms	Number of bedrooms
Full Bathrooms	Number of full bathrooms
Half Bathrooms	Number of half bathrooms
Basement	Equals to one if unit has a basement and zero otherwise
Central	Equals to one if unit has central heating and zero otherwise
Fireplace	Number of fireplaces
New	Equals to one if unit is new and zero otherwise
Age	Age of the unit (in years)
HOA	Equals to one if property has a home ownership association and zero otherwise
	Neighborhood
Density	Population density in Census Block Group (CBG)
Black	Proportion of Blacks in CBG
Hispanic	Proportion of Hispanics in CBG
Greater than 65	Proportion older than 65 in CBG
HS dropouts	Proportion of high school dropouts in CBG
Unemployment	Unemployment rate in CBG
Income	Median household income in CBG (in 1999 thousands $)

Table 2: Descriptive Statistics

Variable	Mean	St. Dev.	Min	Max
Transaction				
Price	525.6	(240.6)	125.0	1,995.0
DOM	49.8	(50.9)	1.0	390.0
Listing				
Virtual	0.75	(0.4)	0.0	1.0
Number of pictures	7.5	(6.5)	0.0	27.0
Seller				
Markup	0.04	(0.1)	-0.7	1.1
Motivated	0.03	(0.2)	0.0	1.0
Vacant	0.36	(0.5)	0.0	1.0
Picture peers	7.36	(2.6)	0.0	20.0
Virtual peers	0.74	(0.2)	0.0	1.0
Housing unit				
Atypicality	0.3	(0.2)	0.0	3.1
Sqft	1,706.0	(817.1)	426.0	9,590.0
Acreage	0.21	(0.46)	0.0	7.6
Bedrooms	3.31	(1.06)	0.0	13.0
Full Bathrooms	2.29	(0.82)	0.0	8.0
Half Bathrooms	0.78	(0.64)	0.0	11.0
Basement	0.70	(0.46)	0.0	1.0
Central	0.94	(0.23)	0.0	1.0
Fireplace	0.91	(0.70)	0.0	5.0
New	0.01	(0.10)	0.0	1.0
Age	26.0	(15.0)	0.0	136.0
HOA	0.62	(0.48)	0.0	1.0
Neighborhood *				
Density	20.8	(21.1)	0.2	237.5
Black	0.08	(0.08)	0.0	0.9
Hispanic	0.10	(0.09)	0.0	0.7
Greater than 65	0.08	(0.06)	0.0	0.5
HS dropouts	0.08	(0.08)	0.0	0.7
Unemployment	0.02	(0.02)	0.0	0.2
Income	86.1	(28.1)	14.5	200.0
Observations	15,675			

* The Census variables' statistics are weighted by the number of homes sold in each Census block-group and do not necessarily represent an accurate description of the whole population of Fairfax County. Instead, they describe only those locations where real estate transactions were made.

Table 3. The determinants of pictures and virtual tours

	OLS Dependent variable is the number of pictures on the listing		Probit (Mg.Effects) Dependent variable equals one if listing displays a virtual tour	
Constant	-15.07	(3.84) ***		
Markup	6.77	(0.54) ***	0.43	(0.04) ***
Motivated	-0.27	(0.26)	0.00	(0.02)
Vacant	-0.89	(0.10) ***	-0.06	(0.01) ***
Picture peers	0.51	(0.02) ***		
Virtual tours peers			0.53	(0.02) ***
Atypicality	-1.09	(0.29) ***	-0.02	(0.02)
Log square footage	2.24	(0.26) ***	0.08	(0.02) ***
Acreage	-0.12	(0.17)	-0.02	(0.01) **
Bedrooms	-0.14	(0.09)	-0.02	(0.01) **
Full Bathrooms	0.17	(0.11)	0.00	(0.01)
Half Bathrooms	-0.03	(0.12)	0.00	(0.01)
Basement	0.58	(0.15) ***	0.02	(0.01) *
Central	0.58	(0.20) ***	0.06	(0.02) ***
One fireplace	0.42	(0.12) ***	0.04	(0.01) ***
More than one fireplace	0.67	(0.20) ***	0.06	(0.01) ***
New	-4.00	(0.52) ***	-0.30	(0.05) ***
Age	-0.04	(0.01) ***	0.00	(0.00)
Age^2	0.00	(0.00)	0.00	(0.00)
HOA	0.23	(0.15)	0.02	(0.01) **
Detached	0.61	(0.27) **	0.05	(0.02) **
Townhome	-0.04	(0.22)	0.02	(0.02)
Density	-0.12	(0.10)	-0.01	(0.01)
Black	-1.36	(1.02)	-0.12	(0.07) *
Hispanic	-1.97	(1.11) *	-0.08	(0.08)
Greater than 65	-1.67	(1.15)	-0.05	(0.08)
HS dropouts	-0.63	(1.34)	-0.07	(0.09)
Unemployment	7.27	(3.43) **	-0.09	(0.23)
Log median household income	0.06	(0.31)	0.00	(0.02)
Dummies for Month/Year (17)	Yes		Yes	
Dummies for Zip Codes (51)	Yes		Yes	
R square	0.160			
Number of observations	15,675			

Standard errors in parenthesis. The covariance matrix was calculated using White Heteroskedasticity-Consistent Method.

*, **, ***, denote significance at the 10, 5, and 1 percent level, respectively.

Marginal effects are evaluated at the sample mean.

Table 4. OLS Results
Dependent variable: Log of transaction price

	(1)	(2)	(3)	(4)	(5)
Constant	6.07 ***	2.93 ***	2.99 ***	1.30 ***	2.47 ***
	(0.01)	(0.05)	(0.06)	(0.09)	(0.07)
Virtual tour	0.010	0.011 ***	0.018 ***	0.011 ***	0.008 ***
	(0.009)	(0.003)	(0.003)	(0.003)	(0.002)
Number of pictures	0.0134 ***	0.0012 ***	0.0016 ***	0.0016 ***	0.0015 ***
	(0.0006)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Log square footage		0.384 ***	0.383 ***	0.342 ***	0.323 ***
		(0.007)	(0.007)	(0.007)	(0.006)
Acreage		0.081 ***	0.082 ***	0.071 ***	0.074 ***
		(0.006)	(0.006)	(0.005)	(0.004)
Bedrooms		0.015 ***	0.016 ***	0.020 ***	0.031 ***
		(0.002)	(0.002)	(0.002)	(0.002)
Full Bathrooms		0.070 ***	0.070 ***	0.060 ***	0.044 ***
		(0.003)	(0.003)	(0.002)	(0.002)
Half Bathrooms		0.024 ***	0.025 ***	0.021 ***	0.016 ***
		(0.003)	(0.003)	(0.003)	(0.002)
Basement		0.076 ***	0.076 ***	0.063 ***	0.062 ***
		(0.004)	(0.004)	(0.004)	(0.003)
Central		0.017 ***	0.016 ***	0.003	0.004
		(0.005)	(0.005)	(0.004)	(0.004)
One fireplace		0.039 ***	0.039 ***	0.028 ***	0.029 ***
		(0.003)	(0.003)	(0.003)	(0.002)
More than one fireplace		0.144 ***	0.145 ***	0.109 ***	0.077 ***
		(0.005)	(0.005)	(0.005)	(0.004)
New		0.052 ***	0.064 ***	0.063 ***	0.017
		(0.016)	(0.016)	(0.015)	(0.013)
Age		-0.008 ***	-0.008 ***	-0.010 ***	-0.011 ***
		(0.001)	(0.001)	(0.001)	(0.001)
Age^2		0.0001 ***	0.0001 ***	0.0001 ***	0.0001 ***
		(0.000)	(0.000)	(0.000)	(0.000)
HOA		-0.035 ***	-0.036 ***	-0.023 ***	0.005 *
		(0.004)	(0.004)	(0.004)	(0.003)
Detached		0.298 ***	0.296 ***	0.283 ***	0.359 ***
		(0.008)	(0.008)	(0.007)	(0.006)
Townhome		0.086 ***	0.083 ***	0.106 ***	0.154 ***
		(0.006)	(0.006)	(0.005)	(0.004)
Dummies for Month/Year (17)	No	No	Yes	Yes	Yes
Census Block Group variables	No	No	No	Yes	Yes
Dummies for Zip Codes (51)	No	No	No	No	Yes
R square	0.050	0.871	0.879	0.901	0.937
Number of valid observations	15,675	15,675	15,675	15,675	15,675

Standard errors in parenthesis. The covariance matrix was calculated using White Heteroskedasticity-Consistent Method.

*, **, ***, denote significance at the 10, 5, and 1 percent level, respectively.

Table 5. OLS Results
Dependent variable: Log of days on the market

	(1)	(2)	(3)	(4)	(5)
Constant	2.93 ***	3.89 ***	3.76 ***	4.71 ***	3.88 ***
	(0.02)	(0.34)	(0.33)	(0.64)	(0.70)
Virtual tour	0.580 ***	0.546 ***	0.503 ***	0.510 ***	0.512 ***
	(0.028)	(0.028)	(0.027)	(0.027)	(0.027)
Number of pictures	0.0015	-0.0015	0.0004	0.0005	0.0003
	(0.0016)	(0.0015)	(0.0014)	(0.0014)	(0.0015)
Markup		2.970 ***	2.568 ***	2.574 ***	2.570 ***
		(0.108)	(0.103)	(0.103)	(0.104)
Atypicality		-0.010	-0.012	-0.029	-0.024
		(0.052)	(0.050)	(0.050)	(0.053)
Log square footage		-0.127 **	-0.105 **	-0.080	-0.095 *
		(0.051)	(0.050)	(0.050)	(0.051)
Acreage		0.040	0.043 *	0.051 *	0.028
		(0.027)	(0.026)	(0.027)	(0.030)
Bedrooms		0.040 **	0.033 **	0.029 *	0.026
		(0.017)	(0.017)	(0.017)	(0.017)
Full Bathrooms		0.008	0.001	0.007	0.016
		(0.021)	(0.020)	(0.020)	(0.020)
Half Bathrooms		0.040	0.027	0.031	0.036
		(0.026)	(0.026)	(0.026)	(0.026)
Basement		-0.068 **	-0.059 **	-0.047 *	-0.041
		(0.030)	(0.028)	(0.028)	(0.029)
Central		0.037	0.053	0.056	0.059
		(0.040)	(0.039)	(0.039)	(0.039)
One fireplace		-0.071 ***	-0.073 ***	-0.062 ***	-0.051 **
		(0.024)	(0.023)	(0.023)	(0.023)
More than one fireplace		-0.089 **	-0.112 ***	-0.088 **	-0.063 *
		(0.036)	(0.035)	(0.035)	(0.035)
New		0.005	-0.061	-0.070	-0.023
		(0.139)	(0.139)	(0.140)	(0.142)
Age		-0.006 ***	-0.008 ***	-0.007 ***	-0.006 ***
		(0.002)	(0.002)	(0.002)	(0.002)
Age^2		0.0001 **	0.0001 **	0.0001 *	0.0001 *
		(0.000)	(0.000)	(0.000)	(0.000)
HOA		0.009	0.014	0.016	0.000
		(0.026)	(0.025)	(0.025)	(0.027)
Detached		-0.134 ***	-0.134 ***	-0.118 **	-0.139 ***
		(0.049)	(0.047)	(0.048)	(0.051)
Townhome		-0.147 ***	-0.155 ***	-0.170 ***	-0.184 ***
		(0.042)	(0.041)	(0.041)	(0.043)
Dummies for Month/Year (17)	No	No	Yes	Yes	Yes
Census Block Group variables	No	No	No	Yes	Yes
Dummies for Zip Codes (51)	No	No	No	No	Yes
R square	0.047	0.114	0.202	0.203	0.208
Number of valid observations	15,675	15,675	15,675	15,675	15,675

Standard errors in parenthesis. The covariance matrix was calculated using White Heteroskedasticity-Consistent Method.

*, **, ***, denote significance at the 10, 5, and 1 percent level, respectively.

Table 6: Regression Results
Two Stage Least Squares

	Dependent variable (1) Log transaction price	Dependent variable (2) Log days on the market
Constant	2.48 ***	3.69 ***
	(0.07)	(0.75)
Virtual tour	0.021 **	-0.198 *
	(0.010)	(0.106)
Number of pictures	0.0017 *	-0.007
	(0.0009)	(0.009)
Markup		2.91 ***
		(0.12)
Atypicality		-0.06
		(0.06)
Log square footage	0.32 ***	-0.01
	(0.01)	(0.06)
Acreage	0.07 ***	0.01
	(0.00)	(0.03)
Bedrooms	0.03 ***	0.01
	(0.00)	(0.02)
Full Bathrooms	0.04 ***	0.01
	(0.00)	(0.02)
Half Bathrooms	0.02 ***	0.04
	(0.00)	(0.03)
Basement	0.06 ***	-0.02
	(0.00)	(0.03)
Central	0.00	0.09 **
	(0.00)	(0.04)
One fireplace	0.03 ***	-0.01
	(0.00)	(0.02)
More than one fireplace	0.08 ***	0.00
	(0.00)	(0.04)
New	0.02 *	-0.27 *
	(0.01)	(0.15)
Age	-0.01 ***	-0.01 **
	(0.00)	(0.00)
Age ^{2}	0.00011 ***	0.00004
	(0.00001)	(0.00004)
HOA	0.00	0.02
	(0.00)	(0.03)
Detached	0.36 ***	-0.09 *
	(0.01)	(0.05)
Townhome	0.15 ***	-0.17 ***
	(0.00)	(0.05)
Dummies for Month/Year (17)	Yes	Yes
Census Block Group variables	Yes	Yes
Dummies for Zip Codes (51)	Yes	Yes
Number of observations	15,669	15,669

Standard errors in parenthesis. The covariance matrix was calculated using White Heteroskedasticity-Consistent Method.

*, **, ***, denote significance at the 10, 5, and 1 percent level, respectively.

The endogenous variables are the number of pictures and the availability of a virtual tour.

Instruments are discussed in the text. We were unable to construct our instruments for six observations and ,thus, the sample size slighlty decresases.