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Abstract

We consider the effect of expertise on economic transactions, with a particular focus on the real estate market. We show that even as listing information becomes increasingly accessible on real estate aggregation websites, realtor expertise remains important in securing a desirable sale price. One main channel for the effects of such expertise is improving information dissemination to potential buyers through higher quality listings. Using listing photos and remarks as measures of quality, we find that realtor activity is correlated with significantly higher quality listings. We then measure the price impact of these measures of quality and find that, even after controlling for a large spectrum of house characteristics, listing quality is correlated with higher sale prices. Additionally, we find that unobserved benefits of expertise such as negotiation or showmanship remain even after controlling for listing quality.

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1 Introduction

Expert agents have traditionally played important roles in facilitating the exchange of goods. For example, travel agents match hotels and flights with potential travelers and realtors match buyers and sellers of houses. Many of these roles have recently come under attack due to the entry of online platforms that provide much of the same information, often at no cost. In some markets, experts have remained resilient to this entry and still play crucial roles in facilitating transactions. We want to study how experts can continue to add value in these markets.

In this paper, we focus on the real estate market, which is particularly suited for this study as ample information is available not only on the goods exchanged but also on the relevant realtors. Realtors are important intermediaries in real estate transactions as they smooth the process of information gathering, match buyers and sellers, and aid in the ultimate negotiation process. They also advertise and market the house by putting up listings on the MLS (Multiple Listing Service) system and real estate web portals such as Zillow, Trulia, and Redfin.[1] Realtor expertise aids in these aspects and also leads to more reliable assessments of the house's value. Simply put, realtors match buyers and sellers for a given property and rely on their expertise of the local market and observable and unobservable characteristics to form their expert opinions.

The entry of internet real estate listing aggregation websites has provided house buyers and sellers with opportunities to bypass agents. Most buyers now start their research on the internet and trim down the number of houses they consider by searching for desired characteristics. Home buyers and sellers can easily access information about properties of interest or comparable properties in their locale or even around the country using Trulia, Zillow, Google maps, and countless other freely accessible online resources. According to the 2014 Real Estate Association Report, "90% of home buyers searched online during their home buying process." By providing easy access to almost all of the houses for sale, website have essentially supplanted much of the realtor's role in the search process.[2] Nonetheless, more than 75% of the potential pool of buyers and sellers still employ realtors. We focus on how the expertise (as measured by realtor activity and realtor experience) of the seller's realtor can contribute to this search process: by providing higher

[1] Ford, Rutherford, and Yavas (2005) show that houses that were listed on the internet take slightly longer to sell but sell for marginally higher prices.

[2] This increasing use of online search has caused industry experts to question the future of realtors (Kasanoff 2014). However, other experts are more optimistic: some say that realtors are nonetheless very important in the real estate market as they help provide additional information and services (e.g., the builder having a reputation for leaky roofs or the granite counter tops having a very slight pitch) that may not be precisely presented in photos or descriptions (Calltharp 2014).

quality listings, expert realtors can improve the dissemination of information to potential buyers. Our paper differs from the existing literature as it explicitly shows how realtor expertise is correlated with higher sale prices through the channel of listing quality.

We measure listing quality by its ability to disseminate information about the house of interest. To do so, we construct three measures of listing quality: number of photos, the median resolution of photos, and the objectiveness of its text remarks. All three measures seek to measure the effectiveness of the listing in information dissemination. Greater numbers of quality photos provide buyers more comprehensive information about a house's features, while having objective as opposed to subjective remarks reduces ambiguities about specific characteristics.

We then show that realtors with more activity are associated with higher quality listings, which are then correlated with increases in the sale price. These results hold even after a rich set of controls on house characteristics (such as square feet, number of bedrooms, number of bathrooms, the age of the house in years, and the average rating of nearby schools), calendar year-quarter fixed effects, zip code fixed effects, city-block fixed effects, and controls for the length of the remark and potential physical upgrades. Finally, we find that the coefficients for objective phrases are larger in magnitude when describing basic features of the house (e.g., kitchen, windows, cabinets, lighting) as opposed to premium features of the house (e.g., fireplace, swimming pool). We interpret these results to mean that objective phrasing is able to better communicate additional information for basic house characteristics. For premium characteristics, their mere existence is sufficient information.

Our results are subject to a number of important limitations, primarily due to the difficulties in identifying causal effects in the presence of unobserved house characteristics. The first limitation concerns our analysis of the relationship between listing quality and realtor experience / activity. The assignment of realtors to properties is unlikely to be random—experienced or active realtors may be more likely to represent houses with more positive unobservable characteristics. Our main concern is that these houses present more opportunities for photos, which could explain part of the correlation we observe between realtor experience / activity and photo quality. We partially address this concern by exploiting the fact that any sell-side realtor also works on the buy-side, where they are likely to transact houses with similar unobservable characteristics, but have no influence on listing quality. Thus, we account for the effects of unobservable characteristics on listing quality by adding the observable house characteristics and listing quality of these buy-side houses as controls. Additionally, we note that photo quality is relatively cheap to produce (even standard smart phones are able to produce high quantities of high-resolution photos), so the realization of listing quality is likely to be more realtor-dependent rather than property-dependent.

The second limitation concerns our results of sale price and time on market on listing quality. Due to unobserved house characteristics, we caution against interpreting the coefficients from these regressions as causal effects. However, note that we partially address these confounds by adding property fixed effects and focusing on the variation between multiple sales of the same property.

Our measures capture listing features considered important by both industry and academic experts. Lewis (2011) also employs quantity of photos and text remarks. He shows that a precise description, regardless of whether it's positive or negative, has a significant effect on the price of cars on average. The effect of descriptions and words in particular has been extensively studied. A 2005 National Bureau of Economic Research study explains that remarks containing words that depict objective attributes like "granite," "maple," or "gourmet" leads to higher sale prices of homes whereas more subjective words, open to anyone's interpretation and preferences, like "clean," "quiet," "fantastic," and "charming" are at best ineffective or worse hurt prices. Haag, Rutherford, and Thomson (2000) find that mentioning "garage," "lake," and "move-in-condition" are associated with increases in the sales price of 9.8%, 5.6%, and 12% respectively. Levitt and Syverson (2008) employ indicators for keywords in the text remark in their analysis. In practice, the 2014 Real Estate Association Report states that, "[t]he quality and number of pictures matter in the impression that potential buyers have of the home they would potentially visit. The pictures serve as a hook to make potential buyers come on a visit of the home." It also mentions how "[g]ood agents would hire a professional photographer to take pictures and process them. MLS usually requires an outside picture. Bad realtors would usually take pictures with their own personal camera or even worse with their cell phones."

Our results contribute to a rich set of literature that empirically examines the effects of the realtor expertise. Waller and Jubran (2012) find that properties listed by experienced realtors (licensed realtors with ten or more years of experience) sell for approximately 2% more than those of inexperienced realtors and usually 32% faster. Munneke and Yavas (2001) present both theoretical and empirical support for their hypothesis that there is no significant difference in listing duration between realtors from full-commission firms and other realtors, even though one might think that realtors from full-commission firms have higher expertise. The authors suggest that the self-selected expert realtors ultimately end up with more listings, which slows down their sales rate to the market average. Levitt and Syverson (2008) and Rutherford, Springer, and Yavas (2005) show that the effects of realtor expertise may only be fully realized when selling their own homes (as opposed to client-owned homes). Salant (1991) and Hendel, Nevo, and Ortalo-Magné (2009) examine whether the realtor expertise is necessary at all by comparing realtor-assisted listings against for-sale-by-owner listings. Barwick and Pathak (Forthcoming) find that realtors are differentiated by experience. This paper provides evidence on how such differentiation may be realized in listing quality.

Perhaps closest to our analysis of photos and text remarks is Lewis (2011), who finds that car dealers post significantly more photos and more frequently use professional listing software than non-dealers selling similar used cars on eBay motors. Additionally, Lewis (2011) finds that dealers sell cars that are more likely to fetch a higher price according to a hedonic regression. Dealers sell newer, lower mileage cars that are more often under warranty, and they employ a revenue-improving strategy of lower minimum bids with higher reservation prices. Non-dealers, on the other hand, often face a higher disclosure cost on the website as there are substantial economies of scale in using professional listing software and in providing an optimal number of photographs to aid the information asymmetry problem. Lewis (2011) also finds that wording in a listing tends to be accurate, even though cars listed with "rust" in the description sell for less than cars with no mention of rust at all, positing that seller reputation and optimal disclosure yield this outcome.

Finally, our results can be interpreted in the scope of a matching and search model of the housing market, such as those in Yinger (1981), Yavas (1992), and Carrilo (2012). In Carrillo (2012)'s model, buyers and sellers search randomly with sellers posting advertisements in hopes of getting prospective buyers to visit and ultimately buy their house. Since physical viewing is costly, this approach makes it critical to sellers to improve listing quality and develop a form of targeted advertising in order to match buyers with desirable preferences. The rise of real estate web portals means that online viewing now always precedes physical viewings, which diminishes the importance of face-to-face "sale" tactics while increasing the importance of ex-ante marketing and information dissemination.

2 Data

We construct a novel dataset of real estate listings and sales from publicly available data from a major real estate website. This dataset covers a total of 40,049 real estate sales from across three states: Arizona, California, and Illinois. For each listing, we capture all of the critical information typically used by a potential buyer before buying a home: size (in square feet), number of bedrooms, number of bathrooms, year built, buyer and seller realtor names, past sale history, school rating, as well as all realtor-uploaded photos and the realtor's text remark. Additionally, we obtain post-sale information such as the final sale date and final price. Table 1 reports summary statistics for some of these variables. Figure 1 shows trends in sale price and time to sale over time. In order to ensure standardization across listings, we restrict our sample to MLS listings.

We construct novel measures of listing quality using the photo and text data. The only other significant aspect of listing quality is the completion of forms related to house characteristics, an activity where expertise is likely to make little difference. (While inexperienced realtors may neglect to fill these characteristics, MLS software requires the most basic information on each listing to be listed. Realtors are unlikely to make factual errors in this process.)[3] Photos and text serve as strong promotional tools for realtors to convince potential buyers of the quality of the house, and often constitute as the house's first impression to buyers. Given that physical viewings are costly for buyers, these first impressions are crucial determinants of physical viewings and thus of the potential sale of the house.

We construct our dataset by first sampling from sold listings from the years 2010 to 2013 randomly picking zip codes within the three states of interest. We then supplement these listings with recent past completed listings from the same houses. In part of our later analysis, we use house fixed-effects, and rely on these past listings to identify our coefficients. In these specifications, we are only able to use houses with more than one observed listing. Of the 40,049 total listings, 9,799 listings satisfy this constraint (henceforth referred to as the "multiple listings sample"). Table 1 reports summary statistics for this subset of listings.

2.1 Measures of listing quality

Due to the high number of listings in our dataset and the fact that photo quality in themselves can be fairly subjective, [4] we use two easily accessible, objective measures instead. The first is the number of photos uploaded, which is readily observable to the potential buyer (real estate web pages often prominently display the total number of photos available right next to the photo display box). Figure 2 shows trends in the number of photos over time. The second is the median resolution of the photos, measured in number of pixels (for example, a standard 640 x 480 photo is computed as 307,200 pixels). This secondary characteristic allows us to measure the quality of uploaded photos, which can vary significantly across listings. Even a high quantity

[3]It is possible for realtors to submit an initial listing without having completed uploading photos to the system. However, this process is typically completed within a few days and not reflected in the final listing information.

[4]Most obvious photo rating measures involve subjective judgment, and even more measurable traits such as angles and lighting still rely on subjective criteria.

of photos can be uninformative at lower resolutions. Note that the MLS system places restrictions on both the number and the resolution of uploaded photos, so both of our measures are bounded from above.[5] Photos of the home listings have also file size requirements, as they must be at least 11KB, and no more than 4MB in size. Despite these limits, there remains enough variation in both number and resolution of pictures for our analysis (while photos of larger resolution will likely be larger in size, 4MB is high enough not to exert any strong effects on resolution). One further complication is that the resolution limit is fixed with respect to orientation (i.e., any portrait photo must include a "letterbox" on the two sides), which means that portrait photos will have much smaller resolution than landscape photos. We avoid this issue by considering only landscape photos in our calculation of the median resolution.

In order to measure the information content of the text remarks, we focus on a few important physical characteristics and manually classify the ways in which they are described. We define two classifications of interest—objective phrases and subjective phrases. In general, an objective phrase corresponds to a value that is inherent in the characteristic itself, i.e., the characteristic has value because it is there: for example, a "gourmet kitchen" corresponds to a type of kitchen, and "cherry cabinets" refers to the type of material of the cabinets. In a way, an objective remark emphasizes that it is costly to produce such an objective characteristic. Objective remarks also represent contractual obligations, as potential buyers can bring a lawsuit in the event of a false claim from the realtor or seller. A subjective characteristic relates to the value attributed by the beholder, here the seller's realtor, rather than the value contained in the characteristic itself. A subjective characteristic is a perception, not a fact: for example, a kitchen defined as "beautiful" or a "cozy" fireplace might be a characteristics debatable between different people.

In the end, we focus on six important physical characteristics: kitchen, window, cabinet, lighting, fireplace, and swimming pool. For each characteristic, we define a dictionary to be the set of all two-word phrases with the characteristic as the second word (e.g., gourmet kitchen, eatin kitchen, spacious kitchen). Within each dictionary, we manually classify phrases as objective or subjective. We also remove phrases that are either uninformative or unrelated, such as "the kitchen" or "a kitchen."

The use of objective and subjective phrasing is central in practice: a study by Point2Homes, a company specializing in real estate marketing, uses a word count study to determine the types of words that increased the value of the home.[6] They list the occurrences of the most used words in descriptions: the very subjective

[5]For an example of such restrictions, see http://portal.mlslistings.com/help/2011/07/13/photo-upload-faq/ (last accessed on 8/2/2014).

[6]See Point2Homes, "The Most Popular Real Estate Listing Keywords", Feb. 14, 2013

word "beautiful" tops the ranks, followed by more objective remarks, like "hardwood floors" and "stainless steel appliances". We hypothesize that a more experienced realtor would emphasize more concrete attributes of the home as they are more marketable compared to more subjective ones. These concrete attributes help the realtor confidently justify a certain price, and potentially lead to a final price not too far away from the list price.

2.2 Measure of realtor expertise

Realtor expertise is central to the seller's choice of realtor due to the effects of disparities in qualities of realtors on the ultimate sales price. Unskilled realtors may result in unfavorable market outcomes—should the seller not get an offer above her reservation price, it may be necessary for her to take the home temporarily off the market (for potential renovations or repaints).[7] Able realtors, on the other hand, obtain higher sale prices due through marketing and negotiation expertise, and may also minimize time on the market (conditional on achieving a desirable sale price). They are also able to advise the seller on an efficient list price to achieve a desirable sale price and make the home marketable to potential buyers.[8] (Note that usually homes sell within 10% of the list price.)

We consider two main characteristics of realtor expertise that complement each other: realtor *activity* and realtor *experience*.[9] We define realtor activity as the total number of sales attributed to the realtor within the same calendar year. While shorter time periods might give a more accurate measure of activity, we use the entire calendar year in order to avoid seasonality effects.[10]

We define realtor experience as the number of days since the realtor's first acquisition of her real estate license. We obtain the date of real estate license acquisition for each realtor using a database from the Arizona Department of Real Estate, so we simply construct the experience variable via name matching, dropping all cases where the match is imperfect or not found. Unfortunately, such data is not easily accessible for California and Illinois, so any later analysis with respect to experience uses only the subset of observations from Arizona that resulted in a full realtor name match, henceforth referred to as the "realtor experience sample". 10,630 of 40,049 observations remain after these exclusions, and table 1 reports summary statistics for this

[7] Delisting a home could be a bad signal for future sales. Potential future buyers might suspect that the seller has unrealistic expectations about the sale price or that problems had come up during inspection.

[8] Spending too much time on the market might make a home seem like a "lemon," therefore realtor expertise is important to make sure home prices are not prohibitively high.

[9] We consider activity and experience as an adaptation of the Mincer wage equation (Mincer 1974).

[10] A potentially better measure could be the total number of past sales throughout all years, but for the present analysis our lack of data availability before 2009 makes difficult to track experience over time.

subset.

3 Empirical Strategy

3.1 Realtor expertise

We assume that the quality of any house listing is an additive function of the house's characteristics and realtor expertise:

$$quality = X\beta + \eta\,(agent\,expertise) + \nu,$$

where X is a vector of physical characteristics (e.g., square feet, number of bedrooms) and state-calendar quarter fixed effects.[11] In our empirical application, we use the most important determinants of a given realtor's expertise: their sale activity and their career experience. It is important to separate both effects as realtors might be assigned a given listing or buyers based on their reputation and the amount of time their past listings stayed on the market, or a combination of both.

We define the sale activity for each realtor by considering (the logarithm of) the number of listings sold by a given realtor within the same calendar year. This captures the realtor's productivity and success rate. Sale activity is an important performance metric for realtors in practice as it is a direct measure of their compensation: realtors are paid roughly half of the commission on a real estate transaction, which is usually between 2% and 6% of the sale price.[12] We define the realtor's career experience as the number of days since their real estate license certification. Experience is central to potential sellers of a home, as seasoned realtors are more likely to have greater market reach and network size. Realtors with more experience are also expected to be better negotiators on average and more knowledgeable about the market.

Our dependent variable is the quality of a given listing.[13] We use in this paper three measures of the quality of a real estate listing: the number of pictures available on the listing, the median number of pixels in all landscape photos, and the prevalence of objective phrases in the listing remark. All three measures capture the ability of the listing to accurately convey information to potential buyers, especially with respect

[11]The fixed effects take into account the potential seasonality and location effects, as well as general trends in the U.S. housing market.

[12]See, for example, Blanche Evans, "Buyers Mad They Can't Cut Threshold Agent Out of the Deal," Realty Times, Aug. 24, 2005.

[13]For the purposes of our analysis, we focus on the quality of a particular listing as it appears on the web, especially with respect to its ability to accurately convey information. Other methods of improving the general quality of a listed home includes last-minute upgrades (e.g., painting the home prior to listings), or increasing the reach of the listing (e.g., placing advertisements on a variety of real estate websites).

to how a particular house is distinguished from other houses with a similar price range or similar amenities. The number of pictures measures the quantity of information that a buyer has access to for getting quick information on features of a particular house. The median number of pixels complements the quantity of pictures in providing more information about the house. Higher-resolution photos serve both as effective communication of physical qualities of the home and as a signal that the sell-side was willing to pay for an experienced photographer.[14] The prevalence of objective phrases in the remark represents the overall quality of the listing: a good listing would be more likely to be emphasized with objective phrases like “gourmet kitchen” whereas a lower quality listing would read more like a “stunning spacious kitchen area”.

One important confound in this approach is that the assignment of realtors to properties is unlikely to be random—more experienced or active realtors may be more likely to represent houses of higher quality. If expert realtors represent houses with better unobservable characteristics, there may be more opportunities for pictures, resulting in a strong correlation between realtor expertise and photo quantity and quality. Addressing this confound requires controlling for the unobservable features of houses that the realtor is typically associated with, especially the effects of these characteristics on photo quality.

We partially address this confound using information about transactions where the seller’s realtor (whose expertise we are exploring) worked as a *buy-side* realtor. If we assume that the realtor’s clients are similar between the sell- and buy-sides, then we would expect the unobservable features of the sell- and buy-side houses to be similar as well. In such a case, the listing quality of these buy-side houses captures the effect of unobservable features on listing quality. In Appendix table 1, we show that for any given realtor, houses where they worked as a sell-side realtor are statistically indistinguishable in terms of observable characteristics from houses where they worked as a buy-side realtor. While we are unable to conduct a similar test for unobservable features, the equivalence of observable features suggests that this finding may be generalizable.

Thus, we define our buy-side transaction controls as follows. For each transaction i, we define the set of buy-side transactions to be all transactions from the same calendar year where transaction i’s sell-side realtor serves as the buy-side realtor. Our control variables are then the mean of the following variables within the set of buy-side transactions: number of photos, the median photo resolution, square feet, number of bedrooms, number of bathrooms, number of parking spots, indicator for short sale, house age in years,

[14]See, for example, Gene Stowe, ”Photographs are Key for Selling Real Estate,” Tribune Business Weekly, Jun. 06, 2011 or Amy Hoak, “The Power of Real Estate Photos,” Chicago Tribune, Sept. 07, 2012.

and average school rating. The table notes to Appendix table 1 provide more details on the construction of these control variables. The primary variables of interest are the controls defined with respect to the quantity and quality of photos, which capture the realized effect of unobservable house characteristics on photo quality.[15]

3.2 House prices

We assume the following hedonic model for house prices:

$$\ln(p) = X\beta + (photo\,quality)\,\gamma + \phi_k\,(obj\,phrase)_k + \varphi_k\,(subj\,phrase)_k + \varepsilon, \quad (1)$$

where X is a vector of house characteristic controls (number of photos, square feet, number of bedrooms, number of bathrooms, whether the sale was a short sale, the age of the house in years, the average rating of nearby schools, and indicators for the existence of a fireplace or pool), *photo quality* is the a vector of photo characteristics (number of photos, median resolution), and $(obj\,phrase)_k$ and $(subj\,phrase)_k$ are indicators for whether characteristic k is described in an objective or subjective way, respectively.[16]

Unbiased estimates of ϕ_k and φ_k rely on confronting a crucial confound: the effects of the physical existence and the value or quality of characteristic k. We address this in two ways. First, our characteristics are either common to all properties (e.g., kitchen, window, cabinet, lighting) or their existence can be easily controlled for (every listing has tick boxes for whether the house has a fireplace or a pool). Moreover, we focus on houses for which we observe multiple sales by adding house fixed effects, effectively restricting the identification of ϕ_k and φ_k to *within-house* variation. We also control for renovation and remodeling effects, and drop all properties where we observe consecutive sales within the same 365 day period. Houses that experience this kind of rapid resale are often rehabilitation project type of homes, later called simply "rehabs," and removing such observations ensures that our objective phrase measures do not pick up the effect of additional features during these "rehabs."[17] These considerations allow us to control for the value or quality of the characteristics. As an additional check, we include in our regression a dummy for whether

[15] While other houses where the realtor worked on the sell-side are also likely to share similar unobservable characteristics, we cannot use the photo quality of such houses as controls as it would become difficult to identify the effect of realtor activity and experience.

[16] While time to sale is likely an important determinant of sale price, we suspect part of listing quality's effect on price is through its effect on time. In order to capture this effect, we do not include time as a control in our baseline specification.

[17] Rehabilitation can mean anything from just the inside of the home needing minor work, to a full rebuilding of the home without altering the floor plan, like new plumbing, electrical systems, windows, roofing, among others.

the word “view”—a feature unlikely to change in time—appears in the remark.

4 Results

Table 2 details the regression estimates of the determinants of listing quality. Each column uses a different measurement of quality. Columns (1)-(2) use as the dependent variable the number of photos, while columns (3)-(4) use the median number of pixels from all landscape photos.[18] Columns (2) and (4) implements the strategy discussed in section 3 and add controls for house characteristics from the sell-side realtor's buy-side transactions. The coefficient for realtor activity is positive and statistically significant for both columns, while the coefficient for realtor experience is somewhat ambiguous. The additional controls in columns (2) and (4) did not change the coefficients for realtor activity significantly, though it did increase the standard errors due to the decrease in power. It is important to note that our measure for realtor experience, time since first acquisition of the real estate license, is highly correlated with age. While we expect realtor experience to positively correlate with listing quality, it may be possible that age is negatively correlated with the listing quality (older realtors may be less familiar with technology, and thus be unable to upload a large number of high quality photos). Additionally, the realtor's experience may not accurately account for the existence of a support team, which may include members with less experience.

Table 3 presents the results of the regressions of the log of sale price on photo quality measures, realtor's sale activity, and realtor experience. For all specifications, we add house characteristic controls (square feet, number of bedrooms, number of bathrooms, number of parking spots, indicator for short sale, the age of the house in years, and the average rating of schools serving the address) and year-quarter fixed effects. Column (1) presents estimates for our baseline specification. The coefficients for both photo quality measures (number of photos and median number of pixels) are positive and significant. Additionally, the coefficients for realtor expertise (realtor activity and realtor experience) remain significant after controlling for photo quality, suggesting that expertise contributes to the final sale price through mechanisms other than photo quality. (For example, experienced realtors may be better negotiators, improve the presentation of the house, or possess larger networks and relationships with realtors, therefore increasing the likelihood that they would have worked with a potential buyer's realtor).

Column (2)-(4) of table 3 explore the identification of our coefficients of interest by adding zip code fixed

[18]Due to the presence of the confound described in the previous section and the scarcity of observations that contain both multiple listings *and* realtor experience data, we are unable to conduct this analysis for the objectiveness of text remarks.

effects, city-block fixed effects and property fixed effects, respectively. We find that both the magnitude and significance of the photo quantity and photo quality coefficients remain similar, though the magnitude of the photo quantity coefficient increases in the specification with property fixed effects. Column (5) adds (the logarithm of) time to sale as an independent variable. We find that the coefficients remain essentially unchanged compared to our baseline specification, which is consistent with the fact that the coefficient for time to sale is essentially zero. Finally, column (6) adds the logarithm of the ratio between sale price and list price as an independent variable. Compared to our baseline specification, the coefficient for realtor activity changed significantly, and the coefficient on the price ratio is negative and statistically significant (i.e., conditional on observable characteristics, houses listed at lower prices tend to sell for less). This suggests that realtors who make large numbers of transactions may list houses at lower prices to facilitate quicker sales. Our results on the quantity of photos used in the listings are similar to those from Lewis (2011), which finds analogous results for automobile auctions.

Table 4 reports the results of regressions of time on market on photo quality measures. With the exception of the change in the dependent variable, columns (1)-(4) are identical in specification to those in table 3. Having higher quality photos is correlated with a decrease in the amount of time on market. Surprisingly, the same correlation for number of photos is opposite in sign—having more photos is actually associated with longer time on market. One explanation for this result is seller behavior. Conditional on house characteristics, sellers who post more photos are choosing to show more characteristics, and are thus likely more confident of such characteristics. Therefore, the seller might have higher expectations for the house's sale price and be more patient in waiting for an acceptable offer. We also find that

Table 5 reports results for regressions of log of sale price on remark quality measures. The addition of house fixed effects results in a significant decrease in the number of observations since only houses for which we observe two or more sales are included. In order to compensate for this decrease, we draw our estimation sample from the entire sample of listings instead of only those for which we have an accurate measure of realtor experience (Arizona). As discussed in section 2, we include indicators for whether characteristics k (kitchen, window, cabinet, lighting, fireplace, and pool) are described using objective or subjective phrases. We also include an indicator for the word "view"—an exogenous quality that is unlikely to change over time. For a majority of the characteristics, the coefficient ϕ_k for objective phrasing is statistically significant and positive. Moreover, they are higher than φ_k, their subjective counterparts. In columns (2) and (3), we add controls for the length of the remark and whether the house received any upgrades. Our qualitative conclusions remain the same after these additions.

The result of the positive and significant coefficients for objective phrases provides evidence that using objective qualifiers to describe house characteristics is correlated with higher sale prices on average. We interpret this as the result of effective communication of details of the house's characteristics, as objective qualifiers highlight salient, intriguing home features to potential buyers. In contrast, subjective qualifiers are left to the appreciation of both the writer and the reader, leaving ambiguities in interpretation. Moreover, we find that the effects of objective phrasing actually differ systematically depending on the characteristic qualified. Premium characteristics such as fireplaces or swimming pools are relatively unaffected by the choice of objective or subjective phrasing. One likely explanation is that the bulk of the buyer's consideration is based on whether such a characteristic exists, and many of the distinguishing features are not often commonly described (for example, few listings state the exact size of a swimming pool). This means that additional levels of distinction will only be appreciated by buyers during home visits. On the other hand, basic characteristics (e.g., kitchen, windows, cabinets, lighting) are associated with significant higher prices in the event of objective phrasing. Since all homes contain such features, it is likely that objective phrasing allows the seller realtor to show how these characteristics differ from those in other homes in the area. We interpret these results to mean that objective phrasing is able to better communicate additional information in the event of basic house characteristics.

We also consider the effect of objective and subjective phrases in aggregate by summing the number of characteristics (out of the six that we consider) that are qualified by objective or subjective phrasing. Due to our cautious approach in classifying phrases as objective or subjective, not all characteristics were classified into one or the other for each listing. In fact, only 37% of listings had one or more classified objective phrase, and only 10% had two or more. Rather than using the absolute number of objective phrases in each listing's remark, we instead create two indicator variables: the first is activated when a particular listing has one objective phrase, and the second is activated when a particular listing has two or more objective phrases. We do the same for subjective phrases. Then, we estimate the same regressions as those from table 5.

The results from regressions on these indicators are presented in table 6. Once again, we find that the coefficients for objective phrases are positive and significant, while those for subjective phrases are statistically indistinguishable from zero. In the specification with our full set of controls, we find that having one characteristic with an objective qualifier is associated with a 2.03% increase in the sale price, while having two or more characteristics with objective qualifiers is associated with a 3.83% increase in the sale price. We caution, however, with extrapolation towards higher number of objectively phrased characteristics, as few observations in our sample had three or more characteristics with objective qualifiers. Additionally, while we have addressed the confounding effects of the physical existence of characteristics, we still caution against causal interpretations of these findings and their magnitudes.

5 Conclusion

Previous research on market expertise focused on efficiency and market clearing conditions; our paper focuses on the added value that market expertise of a sell-side realtor brings to the sale of a home. This study contributes to the existing literature by incorporating three measures of listing quality into the sale price of a home. Our results indicate that realtor activity is associated with higher quality listings, as measured by photo quantity, photo quality, and the objectiveness of text remarks. These higher quality listings are then correlated with higher sale prices on average. We interpret the higher sale prices of objective phrasing compared to subjective phrasing in the text remark of the listing as a result of information dissemination. We propose a similar interpretation for the effects on price from quantity and quality of photos. Moreover, we find evidence suggesting that objective phrases have larger effects when describing basic features of the house (e.g., kitchen, windows, cabinets, lighting) as opposed to premium features of the house (e.g., fireplace, swimming pool). However, we caution against taking these findings as causal effects due to the inherently difficult identification problems that arise as a result of unobserved house characteristics.

Our study leaves a number of areas for future research. One could replace our manual process of classifying objective / subjective phrasing with an automated learning method such as the one employed in Gentzkow and Shapiro (2010). The benefits are twofold—automated methods allow more coverage with respect to the number of phrases classified and may be also less susceptible to bias and errors. The main challenge is finding an an appropriate external source of text, though services that offer upgrades or renovations likely rely on objective contractural obligations and might be useful sources of information for classifying objective phrases. Additionally, listing quality may be more effective when search costs are higher. One could test such a hypothesis with data on determinants of search cost (for example, entry of major listing aggregation websites). Finally, since we expect listing quality to affect prices mainly through its effect on bringing in more potential buyers, having access to a measure of views (e.g., data on open houses) would allow a more direct verification of this mechanism.

Table 1: Summary statistics

Variable	All	Multiple listings sample	Realtor experience sample
Sale price	556,386	518,167	498,607
	(336,380)	(314,958)	(300,452)
Square feet	2,305	2,236	2,764
	(1,111)	(1,016)	(1,133)
Number of bedrooms	3.45	3.40	3.62
	(0.89)	(0.88)	(0.83)
Number of photos	17.91	15.91	23.44
	(12.67)	(12.47)	(14.91)
House age (years)	42.34	40.05	24.47
	(25.17)	(25.84)	(14.76)
Realtor activity			5.10
			(6.82)
Realtor experience			4,110
			(3,094)
Number of listings	40049	9799	10630

Notes: Unit of observation is a sale of a house. Table reports the mean and standard deviations for variables in dataset and two subsets used in estimation. Standard deviations are in parentheses.

Table 2: Realtor activity / experience and listing quality

Realtor characteristics	(1) Number of photos	(2) Number of photos	(3) Photo resolution	(4) Photo resolution
Realtor activity (in logs)	0.4577***	0.5820*	0.0022***	0.0021***
	(0.1379)	(0.2277)	(0.0004)	(0.0006)
Realtor experience (in logs)	0.2003	-0.1829	-0.0009*	-0.0013
	(0.1398)	(0.2653)	(0.0004)	(0.0007)
House characteristic controls	X	X	X	X
Year-quarter fixed effects	X	X	X	X
Controls for house characteristics from sell-side realtor's buy-side transactions		X		X
Mean of dependent variable	23.4461	24.9708	0.2036	0.2078
R^2	0.1511	0.1948	0.6293	0.6279
Number of observations	10630	3629	10630	3629

*** Significant at the 0.1% level. ** Significant at the 1% level. * Significant at the 5% level.

Notes: Unit of observation is a sale of a house. Robust standard errors are in parentheses. Columns (1) and (2) use the number of photos as the dependent variable. Columns (3) and (4) use the median number of pixels (in millions) from all landscape photos as the dependent variable. In columns (2) and (4), we add controls for the sell-side realtor's buy-side transaction characteristics. For each transaction i, we define the set of *buy-side transactions* to be all transactions from the same calendar year where transaction i's sell-side realtor serves as the *buy-side* realtor. We define our control variables to be the mean of the following variables within the set of buy-side transactions: number of photos, the median photo resolution, square feet, number of bedrooms, number of bathrooms, number of parking spots, indicator for short sale, house age in years, and average school rating. These variables serve as controls for realtor-house characteristic interactions. In Appendix table 1, we show that in terms of these observable house characteristics, realtors are statistically indistinguishable in their sell- and buy-side transactions. The table notes also provide more details on the construction of these control variables. In columns (2) and (4), the number of observations drops due to the lack of buy-side transactions in the same year for every realtor.

Table 3: Photos and sale price

Dependent variable: logarithm of sale price						
Listing characteristics	(1)	(2)	(3)	(4)	(5)	(6)
Number of photos	0.0022***	0.0023***	0.0025***	0.0046***	0.0022***	0.0016***
	(0.0002)	(0.0004)	(0.0002)	(0.0008)	(0.0002)	(0.0002)
Median resolution	0.2739***	0.2806**	0.1781**	0.2832	0.2738***	0.3117***
(millions of pixels)	(0.0691)	(0.0914)	(0.0571)	(0.2027)	(0.0692)	(0.0728)
Realtor activity (in logs)	0.0069**	0.0012	-0.0000	0.0163	0.0067*	0.0093***
	(0.0027)	(0.0040)	(0.0021)	(0.0085)	(0.0027)	(0.0027)
Realtor experience (in logs)	0.0186***	0.0129**	0.0024	-0.0104	0.0186***	0.0165***
	(0.0027)	(0.0035)	(0.0022)	(0.0079)	(0.0027)	(0.0028)
Logarithm of time on market					-0.0002	
					(0.0042)	
Log of sale price -						-0.3371**
log of list price						(0.1075)
House characteristic controls	X	X	X	X	X	X
Year-quarter fixed effects	X	X	X	X	X	X
Zip code fixed effects		X				
City-block fixed effects			X			
Property fixed effects				X		
Mean of dependent variable	12.9510	12.9511	12.8869	12.7070	12.9508	12.9926
Number of observations	10630	10629	9004	1574	10621	9586

*** Significant at the 0.1% level. ** Significant at the 1% level. * Significant at the 5% level.

Notes: Unit of observation is a sale of a house. Robust standard errors are in parentheses. Column (1) is our baseline specification and includes characteristics of the house as controls (square feet, number of bedrooms, number of bathrooms, number of parking spots, indicator for short sale, the age of the house in years, and the average rating of schools serving the address) as well as year-quarter fixed effects. Column (2) is the same as (1) but adds zip code fixed effects . Column (3) is the same as (1) but adds city block fixed effects. Column (4) is the same as (1) but adds property fixed effects. Column (5) is the same as (1) but adds the logarithm of time to sale as an independent variable. Note that the number of observations is slightly different due to missing data for time to sale. Column (6) is the same as (1) but adds the logarithm of the ratio between sale price and list price as an independent variable. Note that the number of observations varies due to the addition of fixed effects and missing data for list prices.

Table 4: Photos and time on market

Dependent variable: logarithm of time on market (days)

Listing characteristics	(1)	(2)	(3)	(4)
Number of photos	0.0011	0.0009	0.0005	0.0007
	(0.0005)	(0.0010)	(0.0007)	(0.0024)
Median resolution (millions of pixels)	-0.6329***	-0.5947*	-0.4983*	-2.4609**
	(0.1781)	(0.2080)	(0.2164)	(0.7911)
Realtor activity (in logs)	-0.0325***	-0.0336**	-0.0348***	-0.0402
	(0.0070)	(0.0095)	(0.0088)	(0.0321)
Realtor experience (in logs)	0.0056	0.0039	-0.0014	-0.0143
	(0.0074)	(0.0122)	(0.0090)	(0.0306)
House characteristic controls	X	X	X	X
Year-quarter fixed effects	X	X	X	X
Zip code fixed effects		X		
City-block fixed effects			X	
Property fixed effects				X
Mean of dependent variable	4.4675	4.4673	4.4297	4.2596
Number of observations	10621	10620	8996	1572

*** Significant at the 0.1% level. ** Significant at the 1% level. * Significant at the 5% level.

Notes: Unit of observation is a sale of a house. Robust standard errors are in parentheses. Column (1) is our baseline specification and includes characteristics of the house as controls (square feet, number of bedrooms, number of bathrooms, number of parking spots, indicator for short sale, the age of the house in years, and the average rating of schools serving the address) as well as year-quarter fixed effects. Column (2) is the same as (1) but adds zip code fixed effects . Column (3) is the same as (1) but adds city block fixed effects. Column (4) is the same as (1) but adds property fixed effects. Note that the number of observations varies due to the addition of fixed effects.

Table 5: Effect of remark content on sale price

Dependent variable: log of sale price

Listing characteristics	(1)	(2)	(3)
Kitchen (objective qualifiers)	0.0299***	0.0261***	0.0220**
	(0.0078)	(0.0077)	(0.0075)
Kitchen (subjective qualifiers)	0.0104	0.0072	0.0063
	(0.0075)	(0.0074)	(0.0070)
Window (objective qualifiers)	0.0467***	0.0396***	0.0263**
	(0.0092)	(0.0090)	(0.0085)
Window (subjective qualifiers)	0.0157	0.0099	0.0098
	(0.0147)	(0.0148)	(0.0140)
Cabinet (objective qualifiers)	0.0496***	0.0437***	0.0346***
	(0.0105)	(0.0105)	(0.0100)
Cabinet (subjective qualifiers)	0.0285*	0.0239	0.0173
	(0.0135)	(0.0135)	(0.0127)
Lighting (objective qualifiers)	0.0548***	0.0474***	0.0321**
	(0.0105)	(0.0105)	(0.0099)
Lighting (subjective qualifiers)	0.0140	0.0143	0.0180
	(0.0203)	(0.0203)	(0.0191)
Fireplace (objective qualifiers)	0.0120	0.0066	0.0080
	(0.0071)	(0.0071)	(0.0069)
Fireplace (subjective qualifiers)	0.0000	-0.0077	-0.0040
	(0.0125)	(0.0124)	(0.0119)
Pool (objective qualifiers)	0.0046	0.0017	0.0011
	(0.0079)	(0.0078)	(0.0074)
Pool (subjective qualifiers)	0.0082	0.0048	0.0039
	(0.0131)	(0.0129)	(0.0123)
Indicator for "view"	0.0240**	0.0167*	0.0175*
	(0.0075)	(0.0075)	(0.0074)
House characteristic controls	X	X	X
State-year quarter fixed effects	X	X	X
Property fixed effects	X	X	X
Removes properties with rapid resale	X	X	X
Control for length of remark		X	X
Upgrade controls			X
R^2	0.6160	0.6199	0.6462
Number of observations	9799	9799	9799

*** Significant at the 0.1% level. ** Significant at the 1% level. * Significant at the 5% level.

Notes: Unit of observation is a sale of a house. Robust standard errors are in parentheses. Sample includes all houses with more than one sale in our dataset, excluding those for which we observe consecutive sales within the same 365 day period. Column (1) is our baseline specification and includes controls for house characteristics (number of photos, square feet, number of bedrooms, number of bathrooms, whether the sale was a short sale, the age of the house in years, and indicators for the existence of a fireplace or pool), state-year quarter fixed effects, and house fixed effects. Column (2) is similar to (1), but adds a control for the (logarithm) of the length of the listing remark. Column (3) is similar to (2), but adds controls for possible physical upgrades.

Table 6: Effect of remark content on sale price

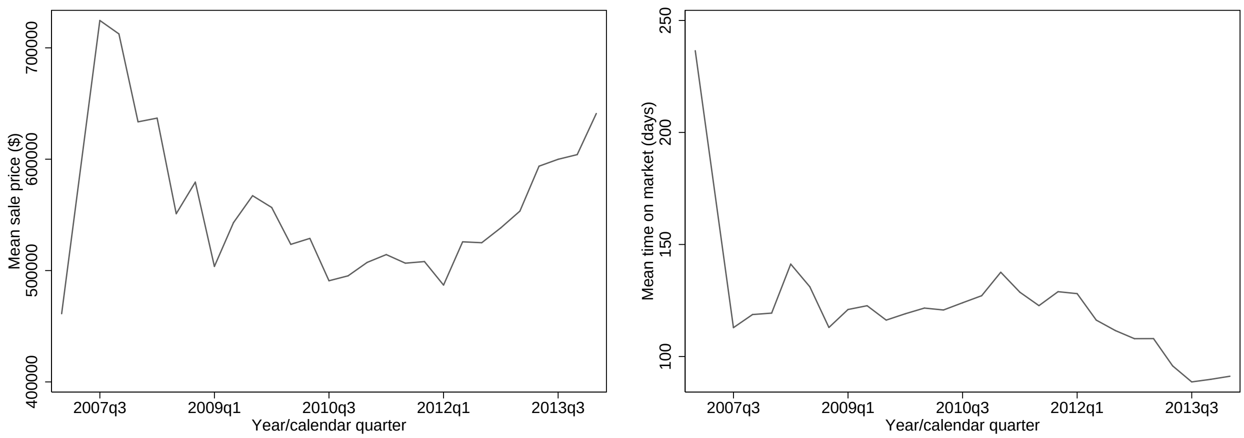
Dependent variable: log of sale price

Listing characteristics	(1)	(2)	(3)
One characteristic with objective qualifier	0.0345***	0.0268***	0.0203***
	(0.0055)	(0.0055)	(0.0052)
More than one characteristic with objective qualifier	0.0601***	0.0499***	0.0383***
	(0.0079)	(0.0079)	(0.0075)
One characteristic with subjective qualifier	0.0133*	0.0086	0.0078
	(0.0059)	(0.0059)	(0.0056)
More than one characteristic with subjective qualifier	0.0252	0.0168	0.0142
	(0.0138)	(0.0137)	(0.0129)
Indicator for "view"	0.0233**	0.0159*	0.0173*
	(0.0075)	(0.0075)	(0.0074)
House characteristic controls	X	X	X
State-year quarter fixed effects	X	X	X
Property fixed effects	X	X	X
Removes properties with rapid resale	X	X	X
Control for length of remark		X	X
Upgrade controls			X
R^2	0.6136	0.6177	0.6451
Number of observations	9799	9799	9799

*** Significant at the 0.1% level. ** Significant at the 1% level. * Significant at the 5% level.

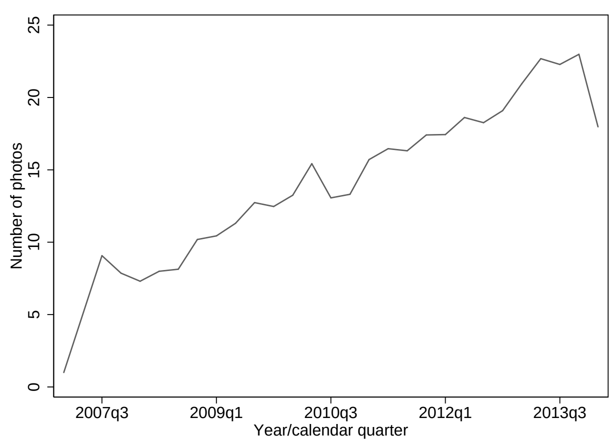
Notes: Unit of observation is a sale of a house. Robust standard errors are in parentheses. Sample includes all houses with more than one sale in our dataset, excluding those for which we observe consecutive sales within the same 365 day period. Column (1) is our baseline specification and includes controls for house characteristics (number of photos, square feet, number of bedrooms, number of bathrooms, whether the sale was a short sale, the age of the house in years, and indicators for the existence of a fireplace or pool), state-year quarter fixed effects, and house fixed effects. Column (2) is similar to (1), but adds a control for the (logarithm) of the length of the listing remark. Column (3) is similar to (2), but adds controls for possible physical upgrades.

Figure 1: Sale price and time on market



Notes: Plots show the average monthly sale price (left) and time on market (right) for observations in the entire dataset. Note that due to the construction of the dataset, the number of observations is much smaller in the first half of the time range than in the second half. Thus, the higher volatility in both plots is expected.

Figure 2: Number of photos



Notes: Plots show the average monthly number of photos for observations in the "realtor experience sample."

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Appendix

Appendix Table 1: House characteristics of realtors' sell-side and buy-side transactions

House characteristics	Seller-side	Buyer-side	*t*-test p-value
Sale price ($)	586,525	586,512	0.9968
Time on market (days)	116.60	117.53	0.4779
Square feet	2,440	2,457	0.1885
Number of bedrooms	3.49	3.48	0.5145
Number of bathrooms	2.79	2.58	0.3614
Number of parking spots	2.81	2.81	0.8401
Indicator for short sale	0.11	0.11	0.7430
House age (years)	40.04	39.85	0.3017
Average school rating	7.78	7.79	0.5527
Number of observations		6466	

Notes: Unit of observation is a realtor-year. Each observation is the mean of a house characteristic across all sell-side transactions or all buy-side transactions by a given realtor for a calendar year. For example, the first row of the "seller-side" column is computed as follows:

$$\frac{1}{n_{rt}} \sum_{rt} \frac{1}{|\mathscr{I}^s_{rt}|} \sum_{i \in \mathscr{I}_{rt}} sale\, price_i,$$

where house transactions are indexed by i, realtors are indexed by r, and years are indexed by t. $\mathscr{I}^s_{rt}$ is the set of all transactions in year t where realtor r served as the sell-side realtor. $|\mathscr{I}^s_{rt}|$ denotes the number of transactions in $\mathscr{I}^s_{rt}$, and n_{rt} denotes the total number of realtor-years (6466). The first row of the "buyer-side" column is computed similarly, but uses instead $\mathscr{I}^b_{rt}$, the set of all transactions in year t where realtor r served as the buy-side realtor. The "*t*-test p-value" column reports the p-value from a paired *t*-test of $\frac{1}{|\mathscr{I}^s_{rt}|} \sum_{i \in \mathscr{I}_{rt}} sale\, price_i$ versus $\frac{1}{|\mathscr{I}^b_{rt}|} \sum_{i \in \mathscr{I}_{rt}} sale\, price_i$ for all observations rt. Note that a number of realtors did not appear within the same year as both a sell-side and buy-side realtor, and were excluded from this analysis.

Appendix Table 2: Effects of descriptive remarks

	Log of sale price		Log of time on market	
Descriptive remark	Estimate	Std. Err.	Estimate	Std. Err.
Foreclosure	-0.0183	0.0135	-0.2117	0.0638
Handyman	-0.0724	0.0401	0.0663	0.1698
Needs	-0.0759	0.0094	0.0389	0.0435
Tlc	-0.0175	0.0118	-0.0104	0.0603
Motivated	0.0099	0.0127	0.1910	0.0696
Potential	-0.0706	0.0112	-0.0048	0.0422
Youthful	0.2225	0.0264	0.4393	0.1228
Close	-0.0021	0.0040	0.0103	0.0190
New	0.0779	0.0051	-0.0402	0.0206
Spacious	-0.0135	0.0045	-0.0153	0.0211
Elegance	0.0414	0.0192	-0.1751	0.0906
Beautiful	0.0303	0.0046	-0.0081	0.0190
Appealing	-0.0109	0.0299	0.2798	0.2044
Renovated	0.0631	0.0129	-0.0970	0.0532
Remodeled	0.0538	0.0046	-0.0553	0.0229
Vintage	0.0153	0.0230	-0.2291	0.0920
Maintained	-0.0159	0.0081	0.0088	0.0435
Wonderful	-0.0087	0.0060	0.0127	0.0292
Fantastic	-0.0066	0.0093	-0.0206	0.0402
Charming	-0.0102	0.0067	-0.0605	0.0316
Stunning	0.0473	0.0105	-0.1161	0.0342
Amazing	0.0004	0.0076	-0.0124	0.0362
Granite	0.0779	0.0048	-0.0282	0.0230
Immaculate	0.0167	0.0092	-0.0270	0.0542
Breathtaking	0.0337	0.0178	0.1244	0.0866
Neighborhood	-0.0065	0.0067	0.0153	0.0249
Spectacular	0.0036	0.0116	0.0098	0.0513
Landscaped	0.0144	0.0068	0.0009	0.0343
Tasteful	0.0227	0.0104	-0.1143	0.0525
Fabulous	0.0071	0.0079	0.0980	0.0363
Leaded	-0.0381	0.0298	0.1618	0.1055
Delightful	-0.0041	0.0175	0.0061	0.0821
Gourmet	0.0126	0.0078	0.0470	0.0387
Copper	0.0427	0.0082	0.0046	0.0373
Corian	-0.0159	0.0189	0.2340	0.0839
Custom	0.0227	0.0067	-0.0243	0.0240
Unique	0.0253	0.0124	-0.1323	0.0544
Maple	0.0230	0.0107	0.1186	0.0542
Newer	-0.0485	0.0060	-0.0014	0.0288
Hurry	0.0134	0.0106	-0.1425	0.0534
Pride	0.0148	0.0122	-0.0077	0.0617

(Continued from above)

Descriptive remark	Log of sale price Estimate	Log of sale price Std. Err.	Log of time on market Estimate	Log of time on market Std. Err.
Clean	0.0236	0.0088	0.0078	0.0461
Quiet	0.0036	0.0065	-0.0440	0.0318
Dream	0.0075	0.0097	-0.0147	0.0407
Block	-0.0098	0.0093	-0.0415	0.0426
Huge	0.0066	0.0054	0.0035	0.0248
Desk	-0.0135	0.0122	0.0500	0.0791
Mint	0.0427	0.0334	-0.1797	0.1555
Stately	0.0342	0.0405	0.1335	0.1602
Needs updating	0.0091	0.0394	-0.1000	0.1513
Estate sale	-0.1033	0.0855	-0.1641	0.1922
As-is	-0.0641	0.0061	-0.1665	0.0277
Bank-owned	-0.0035	0.0102	-0.1905	0.0530
Priced-to-sell	-0.0266	0.0136	-0.0480	0.0635
State-of-the-art	0.0517	0.0350	-0.1289	0.1220
Built-in	-0.0026	0.0066	-0.0285	0.0252
Move-in	0.0284	0.0077	-0.0777	0.0296
House characteristic controls	X		X	
Year-quarter fixed effects	X		X	
R^2	0.6634		0.2074	
Number of observations	12409		12387	

Notes: Unit of observation is a sale of a house. Standard errors are in parentheses. Both columns include characteristics of the house as controls (square feet, number of bedrooms, number of bathrooms, number of parking spots, indicator for short sale, the age of the house in years, and the average rating of schools serving the address) as well as year-quarter fixed effects. The first two columns use the log of sale price as the dependent variable. The last two columns use the log of time on market as the dependent variable.

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