

The Impact of Public Information on Pricing Dispersion and: Evidence from Housing Markets

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Abstract

This paper examines whether free online information reduces information asymmetry in real estate markets. We focus on the absolute list–sale price spread (APS) in residential housing, which we interpret as a reduced-form measure of belief dispersion and informational frictions. Using a dataset of 62,171 transactions from Philadelphia between 2011 and 2018, we study the impact of automated valuation estimates (Zestimates) and listing-level visual disclosure. Our empirical strategy exploits variation in exposure to online information across housing types and over time, including the maturation of Zillow as an information platform. We find that online information significantly reduces APS, indicating improved price discovery. The effects are economically meaningful and concentrated in more heterogeneous housing types, such as detached and semi-detached homes, where valuation uncertainty is greatest. These findings suggest that publicly available digital information compresses pricing dispersion and partially substitutes for traditional informational advantages, thereby enhancing market efficiency in decentralized markets.

1. Introduction

A central question in financial economics is how information asymmetry affects price formation. When market participants hold heterogeneous beliefs about asset values, transactions reflect not only fundamentals but also disagreement, bargaining frictions, and informational advantages. One observable manifestation of these frictions is pricing dispersion. In financial markets, bid–ask spreads capture the wedge between buying and selling prices and serve as a canonical measure of information asymmetry and liquidity. In decentralized asset markets such as real estate, where transactions are bilateral and infrequent, an analogous measure arises from the gap between listing prices and transaction prices.

In this paper, we study pricing dispersion in housing markets and examine whether free online information reduces such dispersion. We focus on the absolute list–sale price spread (APS), defined as the percentage difference between a property's listing price and its final transaction price. We interpret APS as a reduced-form measure of informational frictions and belief dispersion between buyers and sellers. When information asymmetry is high, buyers and sellers disagree more about asset values, leading to wider bargaining ranges and larger deviations between listing and transaction prices. Conversely, improved information should align expectations and compress APS.

The residential housing market provides an ideal setting to study these mechanisms. Housing transactions are characterized by substantial heterogeneity, high transaction costs, and infrequent participation by households, all of which amplify informational frictions. At the same time, transactions are typically intermediated by real estate agents who possess superior information about local markets and comparable sales due to experience and access to proprietary data. As a result, households face considerable uncertainty when forming valuation expectations. Prior work documents that such informational advantages can give rise to agency problems and influence transaction outcomes (Levitt and Syverson, 2008). In this environment, measures of pricing dispersion such as APS provide a natural lens through which to study the interaction between information and intermediation.

Recent technological advances have fundamentally altered the information environment in housing markets. Digital platforms now provide households with free access to information that was previously costly or restricted. In particular, automated valuation models (AVMs) and online listing platforms offer publicly available signals about

property values and characteristics. These innovations raise a fundamental question: to what extent can free online information reduce informational frictions and improve price discovery in real estate markets?

We focus on two primary sources of online information. First, we examine automated valuation estimates provided by Zillow (Zestimates)¹, which use large-scale data and machine learning algorithms to generate property-specific value signals. These estimates are widely accessible and serve as reference points for buyers and sellers when forming valuation expectations. According to Jeon et al (2023), when public information about a property becomes available, the fair market value serves as a reference price point that influences the valuation decisions of buyers and sellers. Second, we use the number of listing photos as a measure of visual information disclosure. Greater visual transparency allows households to better assess property quality, thereby improving the information environment.

Conceptually, the introduction of public signals should improve the precision of beliefs about property values and reduce disagreement between market participants. In a bargaining framework, this implies a narrower range of acceptable prices and a smaller gap between listing and transaction prices. From this perspective, APS plays a role analogous to the bid–ask spread in financial markets, capturing the extent of informational frictions in a decentralized trading environment.

We test these predictions using a dataset of 62,171 residential transactions from Philadelphia between 2011 and 2018. Our empirical strategy exploits variation in exposure to online information across properties, housing types, and time. To address selection concerns, we construct a matched sample of properties with and without Zestimates based on observable characteristics. We further leverage differences in the informational value of online signals across housing types, as well as temporal variation associated with the maturation of Zillow as an information platform.

Our results show that free online information significantly reduces APS. The effects are concentrated in more heterogeneous housing types, such as townhomes, semi-detached, and detached single-family homes, where valuation uncertainty is greatest. In contrast, we find no significant effect of Zestimates for relatively homogeneous assets such as condominiums. We also find that greater visual disclosure, measured by the number of listing photos, is associated with lower APS for most housing types, although this relationship is weaker for detached homes where photo availability exhibits limited variation. Finally, the effects of online information are stronger in the later period, when Zillow was more widely adopted and its estimates were more salient to households.

These findings contribute to several strands of the literature. First, we contribute to the literature on price discovery and information asymmetry by introducing APS as a tractable and economically meaningful measure of informational frictions in housing markets. By focusing on pricing dispersion, we provide a direct empirical link between belief heterogeneity and bargaining outcomes. Second, we contribute to the literature on financial intermediation by showing that improvements in publicly available information reduce pricing dispersion, consistent with a diminished role for informational advantages in shaping transaction outcomes. Third, we contribute to the literature on digital platforms by demonstrating that algorithmic information improves market efficiency by compressing APS in decentralized real estate markets.

The remainder of the paper is organized as follows. Section 2 presents the theoretical framework. Section 3 describes the data. Section 4 outlines the empirical strategy. Section 5 reports the results, and Section 6 concludes.

2. Conceptual Framework

In the housing market, is the presence of information asymmetries lead to heterogeneity in beliefs across market participants. In advisor–client settings and similar environments, differences in access to information, experience, and signal interpretation generate dispersion in valuation expectations. In markets such as housing, where transactions are infrequent and assets are heterogeneous, these informational frictions are particularly pronounced. We conceptualize these frictions through their implications for price formation. When buyers and sellers hold divergent beliefs about asset values, negotiated outcomes reflect a bargaining range rather than a single common valuation. We capture this mechanism using the absolute list–sale price spread (APS), defined as the absolute difference between the listing price and the realized transaction price. Analogous to the bid–ask spread in financial markets, APS provides a reduced-form measure of belief dispersion and informational frictions. Higher APS reflects greater disagreement and uncertainty, while lower APS indicates more precise and aligned valuations.

2.1 Information Asymmetry and Pricing Dispersion in Advisory Settings

A large body of previous research that information asymmetries play a central role in shaping outcomes in advisory and asset markets. In financial settings, differences in information quality, sophistication, and access to data lead to variation in recommendations, investment decisions, and performance (e.g., Barbon et al., 2019; Calcagno and Monticone, 2015; Foerster et al., 2017; D’Astous et al., 2024). These informational frictions imply that market participants form heterogeneous beliefs about asset values.

One stream of literature focuses on information asymmetries in advisor-client relationships: Bolton et al. (2007) investigate information asymmetries between buyers and sellers in the context of financial services. In particular, they investigate the provision of information by sellers of financial services to financially unsophisticated clients. On the one hand, financial advisors have an incentive to direct clients to their own products as opposed to those that suit them better. On the other hand, the advisors may suffer from reputational costs and lost future revenue due to poor financial advice. The authors show theoretically that competition among financial services providers benefits clients in terms of information disclosure. Furthermore, they show that information provided to clients by a third party is beneficial.

Residential housing markets are characterized by significant information asymmetries between market participants, which can influence transaction outcomes (Anglin & Arnott, 1992). Empirical evidence shows that informational advantages affect pricing and timing: agent-owned properties sell at higher prices and exhibit different time-on-market patterns relative to comparable homes (Rutherford et al., 2005; Levitt & Syverson, 2008). More broadly, differences in information about neighborhood and property characteristics contribute to heterogeneity in beliefs and housing market outcomes (Kurlat & Stroebe, 2015). Additional studies highlight how informational frictions and incentives shape market behavior, including differences in marketing effort, pricing strategies, and negotiation outcomes (Bian et al., 2017; Smith et al., 2019; Benjamin & Chinloy, 2000; Clauretie & Daneshvary, 2008). Taken together, this literature suggests that information asymmetries are reflected not only in intermediary behavior but, more importantly, in pricing outcomes, as differences in information and incentives generate dispersion in valuations and transaction prices.

From a broader perspective, the key implication of information asymmetry is not only potential agency conflicts, but also dispersion in valuation expectations. When agents rely on different information sets or interpret signals with varying precision, their beliefs diverge. In real estate markets, such divergence translates into variation in observed transaction outcomes and reduced pricing efficiency. More generally, the literature on price discovery and market microstructure shows that asymmetric information leads to wider bid–ask spreads, reflecting greater uncertainty and disagreement among market participants (Glosten and Milgrom, 1985; Kyle, 1985).

We build on this insight by focusing on pricing dispersion as a direct manifestation of informational frictions. Specifically, we measure the absolute list–sale price spread (APS) as the gap between listing prices and realized transaction prices. Conceptually, APS is analogous to the bid–ask spread in financial markets, capturing the extent of disagreement between buyers and sellers during price formation. Higher APS indicates greater belief dispersion and a wider bargaining range, while lower APS reflects more precise and aligned valuations.

This perspective shifts the emphasis from intermediary behavior to market-level outcomes. Rather than focusing on how advisors or agents act on informational advantages, we examine how differences in the information environment shape belief dispersion and, ultimately, pricing outcomes in the housing market.

2.2 Public Information and the Reduction of APS

Recent technological innovations have expanded the availability of public information in financial and real estate markets. Social media, FinTech, and PropTech platforms provide households with new sources of information that were previously costly or inaccessible. Prior research shows that such information can improve decision-making and market outcomes by complementing or substituting traditional information sources (Cookson et al., 2024; Chen et al., 2014; Jame et al., 2016). For example, social media increased in importance for retail investors (Eliner and Kobilov, 2023). While the trustworthiness of investment information varies based on investor horizon (Schmidt, 2020), Jame et al. (2016) provide evidence that social media and crowdsourced information provide individual investors with an additional source of information. Furthermore, social media provides investors with information that is separate from information provided from financial analysts (Chen et al., 2014). Bai et al. (2025) show that social media impact retirement planning. For the housing market,

In the housing market, online platforms such as Zillow provide publicly accessible signals about property values and characteristics. Automated valuation models (AVMs) generate estimates of property values, while listing platforms provide detailed visual information through photos and descriptions. These public signals reduce uncertainty about asset values and improve the precision of household beliefs. For example, Jeon et al. (2023) show that new online information (Zestimate) has predictive value for outcomes such as selling price, time on market and listing price revisions.

In particular, the impact of public information is expected to depend on the degree of underlying asset heterogeneity. Properties such as condominiums tend to be relatively homogeneous in terms of structure and features, leading to lower baseline uncertainty and smaller dispersion in valuations. In contrast, townhomes, semi-detached, and detached houses exhibit greater variation in characteristics, resulting in higher uncertainty and more dispersed beliefs. In environments with greater heterogeneity, the marginal value of additional information is higher. Public signals such as valuation estimates and photos are therefore expected to have a stronger effect on reducing APS for heterogeneous housing types than for more homogeneous assets.

2.3 Hypotheses

The availability of public online information reduces pricing dispersion. This price spread is conceptually similar to the bid-ask spread in the stock market, which is a proxy for information asymmetries (e.g., Gomez, 2024; Sankaraguruswamy et al., 2013; Greenstein and Sami, 1994; see for a literature review, Callahan et al., 1997). If free online information in form of a Zestimate reduces information asymmetries between agents and home buyers/sellers, we hypothesize the following for the list-sales price spread:

H1: Compared to a property without a Zestimate, the availability of a Zestimate reduces the price spread.

While access to MLS databases is limited to licensed real estate agents, Zillow and other websites obtain information from these databases and make them available to the public. This information also includes photos of a property. Additionally, listing agents directly upload property photos to Zillow and other free real estate websites. Previous studies find the number of photos in an MLS listing to impact housing transaction outcomes (e.g., Luchtenberg et al., 2019; Allen et al., 2015; Benefield et al., 2011). Zahirovic-Herbert et al. (2020) find that the number of photos reduces the likelihood that a home sells above list price. The availability of free photos on platforms such as Zillow provides more information about a property to households and likely further reduces information asymmetries. We consequently hypothesize that

H2: The more photos are available for a property, the lower is the price spread.

Additionally, housing types can differ in their characteristics, which impact information asymmetries. While condos are relatively similar with regards to, for example, architecture, features and layout, townhomes, detached and semi-detached single-family homes can differ significantly in their characteristics. As a consequence, the information environment for homogeneous housing types compared to more heterogeneous types is better for households, which is expected to reduce the added informational value from free online information. We therefore hypothesize

H3a: Compared to a property without a Zestimate, the availability of a Zestimate for a more heterogeneous housing type (e.g., townhome, semi-detached, detached) reduces the price spread more than for a condo.

H3b: The more photos are available for a more heterogeneous housing type (e.g., townhome, semi-detached, detached) reduces the price spread more than for a condo.

3. Data

3.1 Geographical Study Area

For our empirical investigation, we use 62,171 residential transactions data over the period of 2011 to 2018 obtained from the Multiple Listing Service (MLS) for Philadelphia, PA. The MLS dataset has similar information to what is freely accessible on Zillow and includes list price, sales price, property-level characteristics (e.g., size, bedrooms, bathrooms, garage, pool) and seller/deal characteristics (e.g., distressed sale, motivated seller).

The use of the Philadelphia housing market has several advantages for our investigation: First, as a large metropolitan housing market, Philadelphia offers a high number of housing transactions without any confounding regulatory changes during our sample period. Second, Philadelphia exhibits significant demographic and socioeconomic heterogeneity across neighborhoods, for example, in terms of income, education, and homeownership rates. This variation ensures a high reliance of households on residential real estate agents and

information asymmetries between client and advisor as households purchase houses infrequently and possess limited local market knowledge.

Third, Philadelphia's housing market is highly heterogeneous and dominated by different housing types. In particular, townhomes can be found alongside semi-detached and detached single-family homes within close geographic proximity. In our sample, townhomes represent 66% of all observations, followed by semi-detached single-family homes (17%), condominiums (9%) and detached single-family homes (8%). Properties vary widely in age, renovation history, and architectural features, which generates valuation uncertainty across the more heterogeneous housing types. This feature provides a suitable empirical setting for testing heterogeneity, which predicts that the value of free online information is greater for heterogeneous assets (e.g., townhomes, semi-detached and detached homes) than for relatively homogeneous condominiums. Together, these characteristics make Philadelphia an appropriate empirical laboratory for our investigation into the impact of free online information on information asymmetries between advisors and households. While our study focuses on a single metropolitan area, we consider our finding generalizable to other cities in the US as they have similar market structures and brokerage practices.

3.2 Dependent Variable

Before deriving our variables, we drop data from our sample if the reported time on market plus 1 is less than one day or greater than 365 days to control for potential data error. Then, for each closing year, data is removed if either list price or close price is at or outside of 1% and 99% quantiles. We further cleansed the data for missing house characteristics, which are needed in our analysis. Additionally, we remove outliers including houses with fewer than 1 or more than 15 bedrooms or bathrooms, as well as those aged over 100 years.

Our dependent variable proxying for information asymmetries is the price spread (*APS*). It is defined as the absolute value of list price less sales price for a particular property divided by the list price and multiplied by 100. The absolute price spread reflects the degree of pricing uncertainty surrounding a transaction and captures the extent of informational frictions in the negotiation process. A narrower spread indicates that the transaction price is more closely aligned with the initial listing price. This suggests a reduced uncertainty about the house's value extracted by better-informed parties during bargaining. In this sense, the price spread summarizes the precision of price discovery rather than the direction of price movements.

This interpretation closely parallels the role of bid–ask spreads in financial markets. In market microstructure theory, bid–ask spreads arise from adverse selection, inventory risk, and order-processing costs with information asymmetries playing a central role (Glosten and Milgrom, 1985; Demsetz, 1968). When informed traders possess private information, market makers widen spreads to protect themselves against adverse selection. Conversely, the release of public information reduces informational advantages, intensifies competition among liquidity providers, and leads to narrower spreads (Diamond and Verrecchia, 1991; Copeland and Galai, 1983).

Although housing markets differ from the stock or bond market, similar mechanisms exist. List prices function as posted quotes while transaction prices reflect negotiated outcomes, and the dispersion between the two captures uncertainty about valuation and bargaining power (Lin and Vandell, 2007; Jud et al., 1995). When households face greater uncertainty or rely more heavily on advisors with superior information, negotiations are more likely to result in larger deviations between list and sale prices. In contrast, improvements in the information environment such as the availability of free online value estimates or photos reduce uncertainty and compress price dispersion.

A wider price spread can therefore be interpreted as reflecting higher intermediation costs and informational rents earned by agents, who possess superior market knowledge. A reduction in the absolute price spread following the introduction of free online information is consistent with a decline in these rents and a tightening of the pricing band around fundamental values. This interpretation aligns with evidence from financial markets showing that enhanced disclosure, transparency, and algorithmic information provision improve price efficiency and reduce trading frictions (Sankaraguruswamy et al., 2013; Greenstein and Sami, 1994). Accordingly, in the context of housing transactions, the absolute list–sale price spread is analogous to the bid–ask spreads in financial markets and serves as an empirical proxy for information asymmetries.

3.3 Independent Variables

Our independent variables of interest are free online information, which we proxy for with 1) Zestimates from Zillow and 2) the number of photos associated with a transacted property. In our sample, Zestimates are widely available from 2011. It is important to note that not all properties have Zestimates. For some properties, these value estimates may not be available due to a lack of comparable properties or when the properties are designated as rentals. Furthermore, Zestimates are typically not provided for properties at either the very low or very high end of the price range (Jeon et al., 2022). We derive a binary variable (*Online Estimate*) if a Zillow estimate is available for a property, and zero otherwise. Additionally, we obtain the number of photos for a transaction to create *Photo Count*.

While we cannot ensure a household used Zillow as a source of information, the market dominance of Zillow in the residential real estate market increases the chance that homebuyers and sellers visited the website and obtained free information such as the Zestimate. Zestimates became available in 2006, however, the usage of Zillow by households evolved over time. For example, in 2014, Zillow had 76 million users per year while in 2024 it had grown to 228 million². To provide more insights into the use of free online information by households over our sample period, we conduct a Google trend analysis. In particular, we obtain information for the search term “Zillow” in Philadelphia over the period 2005 to 2018. As shown in Fig. 1 the search for Zillow in Google increased consistently from 2011 to 2014 and then plateaued from 2015 to 2018.

[Insert Fig. 1]

We control for several property-, transaction- and market-level variables that affect *APS*. At the property-level, we control for characteristics such as property age, defined as difference between year of sale and year built, size in square feet, number of bedrooms and bathrooms. We also include binary variables for garage, pool, fireplace, view, and basement, coded 1 if the respective characteristic is present and 0 otherwise.

Control variables also include binary variables for flipping, renovation, upgrade, new construction, motivated seller, and distressed sale. We derive these variables as follows: Properties sold within two years of a previous sale are classified as flips (Wong et al., 2022). Given the average construction year, it is expected that a substantial share of the properties in our sample have undergone renovations. Using the listing text section of the MLS dataset, we identify renovated properties based on keywords such as “renovation,” “remodeled,” and “rehab.” Similarly, we identified new construction by searching for terms such as “to be built”, “newly constructed”, “brand new home”, and “newer construction”. We also account for distressed properties such as foreclosures, short sales, and real estate owned (REO) properties identified in listing texts. Following Glower et al. (1998), we include a binary variable for motivated sellers, defined as those offering price reductions or selling bonuses, to capture seller heterogeneity.

We also control for whether a transacted property was owned by a real estate agent. Our study defines agent-owned properties broadly to include not only those directly owned by real estate agents but also those held by their immediate family members, including spouses, parents, children, siblings, grandparents, and grandchildren, who share financial interests or benefit from the agent's informational advantage. In Philadelphia, state law and MLS rules require agents to disclose any personal ownership interests in a property directly in the MLS listing. The NAR Code of Ethics (Article 4) expands on this, mandating written disclosure for any interest, which includes properties owned by immediate family (e.g., spouses, parents, children). These family relationships are considered a potential conflict of interest. To comply, agents must provide this disclosure in writing, and the professional standard is to place it in the MLS remarks section to ensure all other agents are aware.

Our expanded definition recognizes that a real estate agent typically possesses superior knowledge regarding the property's value and the local market conditions compared to the seller (Levitt and Syverson, 2008) or other buyers. Furthermore, agents bring valuable networks, extensive experience, and improved bargaining power (Xie, 2018). Consequently, individuals with family ties or other affiliations with real estate agents may enjoy these advantages when purchasing a home. This broader classification led to approximately 3% of transactions in our dataset to be classified as agent owned.

We also control for the close price of a transaction for the following reason: Our dependent variable is price spread (in percentage) relative to the listing price. In the stock market, shares trade at a fraction of a firm's value, and investors can manage the exposure to the firm by adjusting the size of their investment in the firm. However, in real estate, the transaction covers the entire property, which makes the value of the property a critical consideration. To ensure we capture the relationship of our independent variables of interest and *APS* when properties have the same value, we include close price as a control variable. We control for sale time by including the log of time on market (*TOM*). To control for market liquidity, we include the quarterly transactions count at the census block group (*CBG*) level, which is referred to as the dissemination area in Canada. Table 1 presents our summary statistics.

Table 1
Summary Statistics

Variable	Mean	Median	Std. Dev.	Min	Max
Close Price	217.04	175	49.50	12	1,360
List Price	223.92	179.9	55.00	14	1,400
Abs(Price Spread)	5.01	3.06	6.87	0	174.25
Online Estimate	0.93	1	0.26	0	1
Photo Count	16.38	18	8.02	0	48
Transaction Volume	13.98	12	9.36	1	77
TOM	57.28	32	65.64	1	365
Agent Owned	0.03	0	0.17	0	1
Flip	0.22	0	0.41	0	1
Renovation	0.21	0	0.41	0	1
Upgrade	0.24	0	0.43	0	1
New Construction	0.11	0	0.31	0	1
Motivated	0.08	0	0.28	0	1
View	0.003	0	0.06	0	1
Condo	0.09	0	0.29	0	1
Townhome	0.66	1	0.47	0	1
Semi-detached	0.17	0	0.38	0	1
Detached	0.07	0	0.26	0	1
Age	63.39	69	29.28	1	100
Size (SF)	1,410.14	1,261	537.28	301	14,676
Beds	2.91	3	0.75	1	15
Bathrooms	1.98	2	0.89	1	10

Notes: This table provides the summary statistics for the sample of 62,171 housing transactions from Philadelphia, PA over the period of 2011 to 2018. Close Price is closing price in \$1,000. List Price is list price in \$1,000. TOM is time on market in days. Abs(Price Spread) or APS is the absolute value of Price Spread, where Price Spread is (List Price – Close Price)/List Price×100. Online Estimate is coded 1 if a Zestimate is available for the respective property. Photo Count is the number of photos per total rooms (beds and bathrooms) in the respective MLS listing. Transaction Volume is the number of transactions in a census tract. TOM is the time on the market of the property. Agent Owned is the property owned by an agent. Flip indicates a sale by a flipper. Renovation indicates a home with renovations. Upgrade indicates the home has been upgraded. New Construction indicates newly built house. Motivated indicates motivated seller remarks. View indicates that the house has a desirable view. Condo, townhome, semi-detached, and detached are coded 1 for the respective housing type. Condo single-family homes represent the reference group. Age indicates the age of the property in years. Size is the size of the house in square feet. Beds and Bathrooms are the number of bedrooms and bathrooms respectively. Garage, Pool, Fireplace, and Basement are coded 1 to indicate the house has those amenities. Distressed indicates a distressed sale.

Variable	Mean	Median	Std. Dev.	Min	Max
Garage	0.42	0	0.49	0	1
Pool	0.06	0	0.23	0	1
Fireplace	0.05	0	0.21	0	1
Basement	0.86	1	0.35	0	1
Distressed	0.06	0	0.24	0	1

Notes: This table provides the summary statistics for the sample of 62,171 housing transactions from Philadelphia, PA over the period of 2011 to 2018. Close Price is closing price in \$1,000. List Price is list price in \$1,000. TOM is time on market in days. Abs(Price Spread) or APS is the absolute value of Price Spread, where Price Spread is (List Price – Close Price)/List Price×100. Online Estimate is coded 1 if a Zestimate is available for the respective property. Photo Count is the number of photos per total rooms (beds and bathrooms) in the respective MLS listing. Transaction Volume is the number of transactions in a census tract. TOM is the time on the market of the property. Agent Owned is the property owned by an agent. Flip indicates a sale by a flipper. Renovation indicates a home with renovations. Upgrade indicates the home has been upgraded. New Construction indicates newly built house. Motivated indicates motivated seller remarks. View indicates that the house has a desirable view. Condo, townhome, semi-detached, and detached are coded 1 for the respective housing type. Condo single-family homes represent the reference group. Age indicates the age of the property in years. Size is the size of the house in square feet. Beds and Bathrooms are the number of bedrooms and bathrooms respectively. Garage, Pool, Fireplace, and Basement are coded 1 to indicate the house has those amenities. Distressed indicates a distressed sale.

[Insert Table 1 here]

4. Identification Strategy and Estimation Method

An empirical challenge in assessing the effects of online information on information asymmetries is that the availability of free online information in form of Zestimates and/or photos is not randomly assigned across listings. Properties with richer online information may differ systematically from other properties along both observable and unobservable dimensions such as property condition, seller sophistication, and agent marketing effort. Consequently, naïve comparisons between properties with and without online information may conflate the effects of information provision with selection into coverage or disclosure intensity.

To mitigate concerns related to non-random assignment of online information, we adopt an empirical approach that leverages multiple sources of variation: First, we exploit systematic differences in the heterogeneity across housing types, which vary in valuation uncertainty and private information. Second, we match properties with similar characteristics to ensure that comparisons are made between similar properties. Third, we incorporate fixed effects at the CBG and year-quarter levels to absorb unobserved spatial heterogeneity and common market trends that may jointly affect online information availability and pricing outcomes. Last, we exploit temporal variations in the adoption of online housing platforms such as Zillow by estimating models across sub-periods. This approach enables us to distinguish the effects of information availability from changes in the Zillow platform usage over time. Taken together, these complementary strategies substantially strengthen identification and support an interpretation centered on information transmission rather than unobserved property characteristics or coincidental market dynamics.

To assess whether the presence of free online information in form of the Zestimate and photos reduces information asymmetries as proxied for by the price spread, we estimate the price spreads (APS) using *Online*

Estimate, *Photo Count* and control variables as shown in Eq. 1. We use year-quarter and census block group fixed effects

$$APS_s = \alpha_s + \beta_{s1} \text{Online Estimate} + \beta_{s2} \text{Photo Count} + C\Gamma_s + Q\Theta_s + L\Lambda_s + \epsilon_s. \quad (1)$$

Where *APS* is the spread between list price and sales price for transaction *s* while *Online Estimate* is coded 1 if a Zestimate was available for the property and *Photo Count* is the number of photos associated with a transacted property. *C* is a vector of our control variables, *Q* is a vector of closing year-quarter indicators, and *L* is CBG level fixed effects.

5. Results

5.1 Baseline Effects of Online Information on Pricing Dispersion

Figure 2 visualizes the quarterly average *APS* over the period of 2011 to 2018. The figure provides evidence that the magnitude of *APS* has decreased over time, which may be due to a reduction in information asymmetries as a result of free online information and an increased usage of this information by households.

[Insert Fig. 2 here]

Our results for the full sample are presented in Table 2. Hereby, Column 1 presents our baseline results without accounting for liquidity measures and free online information in form of *Photo Count* and *Online Estimate*. Column 2 presents the results accounting for market liquidity while Column 3 presents the results for our full model in Eq. 1.

Table 2
Results for APS (Full Sample)

	(1) Baseline			(2) With Liquidity			(3) With Liquidity and Online Information		
	Coef.		t-stat	Coef.		t-stat	Coef.		t-stat
Online Estimate							-0.15		-1.32
Photo Count							-0.11	***	-29.93
Log(Trans. Vol _{cbg})				-0.15	**	-2.28	-0.16	**	-2.46
Log(TOM)	0.34	***	16.63	0.34	***	16.61	0.40	***	19.93
Close Price	-0.02	***	-41.90	-0.02	***	-41.88	-0.02	***	-37.76
Agent Owned	-0.48	***	-3.15	-0.48	***	-3.16	-0.55	***	-3.65
Flip	-0.60	***	-8.89	-0.61	***	-8.91	-0.52	***	-7.74
Renovation	-1.30	***	-19.31	-1.30	***	-19.29	-1.09	***	-16.28
Upgrade	-1.22	***	-19.76	-1.22	***	-19.78	-0.93	***	-15.09
New Construction	-0.54	***	-3.43	-0.53	***	-3.37	-0.65	***	-4.19
Motivated	-0.07		-0.80	-0.07		-0.81	0.00		-0.01
View	0.60		1.31	0.59		1.30	0.69		1.53
Townhome	0.50	***	3.13	0.50	***	3.12	0.53	***	3.33
Semi-detached	0.20		1.08	0.20		1.08	0.27		1.49
Detached Single Family	1.42	***	7.07	1.42	***	7.06	1.45	***	7.26
Log(Age)	0.14	***	3.12	0.14	***	3.09	0.17	***	3.78
Log(Size)	2.72	***	18.08	2.71	***	18.07	2.73	***	18.31
Beds	0.19	***	3.48	0.19	***	3.45	0.12	**	2.23
Bathrooms	-0.28	***	-6.28	-0.27	***	-6.26	-0.18	***	-4.14
Garage	0.10		1.56	0.10		1.55	0.09		1.35
Pool	0.59	***	4.09	0.59	***	4.09	0.60	***	4.20
Fireplace	-0.04		-0.26	-0.04		-0.27	-0.01		-0.08
Basement	0.07		0.61	0.07		0.61	0.13		1.17
Distressed	2.66	***	24.07	2.66	***	24.07	2.38	***	21.62
Closing Year-Quarter FE	Yes			Yes			Yes		

Note: This table reports the estimation results on Abs(Price Spread) or APS. Variables are defined in Table 1. Cbg level locational fixed effects are controlled. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels of confidence, respectively.

	(1) Baseline		(2) With Liquidity		(3) With Liquidity and Online Information	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
CBG FEs	Yes		Yes		Yes	
Adj R^2	0.17		0.17		0.19	
Obs.	62,171		62,171		62,171	
<i>Note: This table reports the estimation results on Abs(Price Spread) or APS. Variables are defined in Table 1. CBG level locational fixed effects are controlled. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels of confidence, respectively.</i>						

Our results for the aggregated housing types in Table 2 (Column 3) suggest that free online information in the form of Zestimates has no effect on the price spread (APS). One explanation for our result for *Online Estimate* is that the impact of Zestimates on price spread varies across housing types due to their varying degrees of heterogeneity. We further investigate this explanation in subsequent sections. Free online information in the form of the number of photos provided on the other hand significantly reduces it, which provides support for *H2*.

The results for our control variables are in line with expectations. A higher transaction volume at a CBG reduces the price spread. More transactions provide housing market participants with more and better information, which reduces information asymmetries. Furthermore, if a property was owned by a real estate agent or family members, the price spread is significantly lower. This is in line with the expectation that they have superior information about housing markets and take advantage of this informational advantage, as suggested by previous research (Smith et al., 2019; Bian et al., 2017; Levitt and Syverson, 2008); Rutherford et al., 2005). Information about property characteristics such as renovation, flipping, upgrade or new construction also reduce the price spread as they represent valuable information to households. More complexity with regards to a property, seller or deal such as time on market, detached single-family or townhome, age, size, pool, number of beds or a distressed sale increase the price spread.

[Insert Table 2 here]

5.2 Heterogeneity by Housing Type

To investigate whether the informative value of free online Zestimates varies across housing types of varying levels of heterogeneity, we separately estimate our results for the model in Eq. 1 for each housing type and present the results in Table 3.

Table 3
Results for APS (Full Sample) Separated by Housing Type

	(1)		(2)			(3)			(4)		
	Condo		Townhome			Semi-Detached			Detached		
	Coef	t-stat	Coef	t-stat		Coef	t-stat		Coef	t-stat	
Online Estimate	0.05		0.39		-0.35 **	-2.10		-0.04	-0.13	-1.03 **	-2.40
Photo Count	-0.02 ***	-3.35	-0.11 ***	-23.80	-0.06 ***	-7.66		-0.07 ***	-5.16		
Log(Trans. Vol _{cbg})	-0.07		-0.55		-0.19 **	-2.18		0.10	0.74	-0.22	-1.00
Log(TOM)	0.45 ***	10.78	0.40 ***	15.12	0.29 ***	6.39		0.41 ***	5.98		
Close Price	-0.004 ***	-6.23	-0.02 ***	-31.40	-0.05 ***	-30.33		-0.02 ***	-13.84		
Agent Owned	-0.07		-0.18		-0.74 ***	-3.94		0.27	0.76	-0.22	-0.39
Flip	-0.13		-0.66		-0.60 ***	-7.11		0.05	0.29	0.17	0.66
Renovation	-0.42 **	-2.54	-1.22 ***	-13.97	-0.21	-1.47		-0.42 *	-1.88		
Upgrade	0.00	0.02	-1.15 ***	-13.78	-0.25 **	-2.03		-0.59 ***	-3.08		
New Construction	-0.59 **	-2.20	-0.61 ***	-3.05	1.06 **	2.08		-0.36	-0.56		
Motivated	-0.11	-0.45	0.04	0.37	0.01	0.07		-0.42 *	-1.67		
View	0.11	0.26	0.74	0.77	0.62	0.58		1.29	0.67		
Log(Age)	0.09	0.96	0.11 *	1.89	-0.58 ***	-3.92		0.30 *	1.78		
Log(Size)	2.07 ***	6.12	2.93 ***	14.10	3.51 ***	10.18		2.24 ***	5.52		
Beds	-0.23	-1.59	0.01	0.19	0.22 *	1.92		0.10	0.83		
Bathrooms	-0.22 *	-1.66	-0.19 ***	-3.25	0.17 *	1.86		0.56 ***	3.99		
Garage	-0.13	-0.76	0.14	1.55	0.38 ***	2.70		0.19	0.96		
Pool	0.37 **	2.17	0.59 *	1.75	-0.38	-1.02		0.21	0.69		
Fireplace	-1.08 **	-2.16	-0.15	-0.76	0.69 ***	2.76		0.51 *	1.68		
Basement	0.04	0.20	0.33 **	2.03	0.62 **	2.00		-0.17	-0.63		
Distressed	1.03 ***	3.43	2.58 ***	18.45	1.13 ***	4.70		0.92 **	2.36		
Closing Year-Quarter FE	Yes		Yes		Yes			Yes			
CBG FEs	Yes		Yes		Yes			Yes			

*Note: This table reports the estimation results of equation on Abs(Price Spread) or APS by housing type. Variables are defined in Table 1. CBG level locational fixed effects are controlled. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels of confidence, respectively.*

	(1)		(2)		(3)		(4)	
	Condo		Townhome		Semi-Detached		Detached	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Adj R ²	0.19		0.20		0.21		0.17	
Obs.	5,794		41,168		10,805		4,404	
Note: This table reports the estimation results of equation on Abs(Price Spread) or APS by housing type. Variables are defined in Table 1. CBG level locational fixed effects are controlled. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels of confidence, respectively.								

Our results for *Online Estimate* suggest that the insignificant coefficient in Table 2 was indeed driven by differences among housing types: For detached single-family homes and townhomes, free online information has a significantly negative relationship with the price spread. These results provide support for *H1*. On the other hand, the coefficients on *Online Estimate* are insignificant for condos and semi-detached homes. While this result was expected for the most homogeneous housing type, condos, and provides support for *H3a*, the result for semi-detached homes is unexpected. We further assess the robustness of our results in Table 3 in the remainder of this study to provide an explanation for our findings for semi-detached homes.

The number of photos available for a property (*Photo Count*) negatively affects the price spread, irrespective of housing type. Thus, the higher the number of photos associated with a property, the lower the price spread. This is in line with our results in Table 2, and the expectation that more photos provide households with more information on a property and reduce information asymmetries between agents and households (*H2*). Compared to more homogeneous condos, more heterogenous townhomes, semi-detached and detached have greater impact of number of photos in reducing APS (*H3b*).

[Insert Table 3 here]

Our results in Table 3 are based on properties within a housing type that may vary significantly in their characteristics, which may explain our unexpected findings for *Online Estimate* and semi-detached homes. To further investigate variations within housing types as an explanation for our previous findings, we employ a quasi-experimental design. In particular, we use a characteristics-matching approach that matches each property without *Online Estimate* (subject) with other properties with similar features (control). The matched control properties must be the same property type and the same sale closing year as the subject. Also, the property size, sale price and property age must be within $\pm 20\%$ range. This process matches one or multiple control properties to a subject property without allowing duplicated matched control properties in the matched data.

Table 4 presents our results for the matched sample, separated by housing type. While the coefficient on *Online Estimate* for condos remains insignificant, the coefficients on this variable are significantly negative for the more heterogenous housing types (townhomes and detached single-family homes). Our results for *Online Estimate* in Table 4 support *H1* and *H3a*. However, the coefficient on *Online Estimate* for semi-detached homes remains insignificant. One explanation for this result is that we aggregate two periods that differed in the usage of Zillow by households in our analysis, which may hide the effect of this variable on the price spread. We further investigate this explanation in the remainder of this study. The coefficients on *Photo Count* are significantly negative for all housing types, which is in line with Table 3 and *H2*.

Table 4
Results for APS (Matched Sample) Separated by Housing Type

	(1)		(2)		(3)		(4)	
	Condo		Townhome		Semi-Detached		Detached	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Online Estimate	0.00	-0.01	-0.53 ***	-3.27	-0.25	-0.84	-0.76 *	-1.89
Photo Count	-0.03 ***	-3.81	-0.09 ***	-18.11	-0.04 ***	-3.84	-0.04 **	-2.46
Log(Trans. Vol _{cbg})	-0.21	-1.46	-0.08	-0.88	0.36 **	2.15	-0.28	-0.93
Log(TOM)	0.48 ***	11.18	0.37 ***	13.28	0.33 ***	6.18	0.35 ***	3.81
Close Price	-0.004 ***	-5.29	-0.02 ***	-31.96	-0.05 ***	-23.12	-0.02 ***	-7.20
Agent Owned	0.26	0.66	-0.58 ***	-2.95	0.53	1.30	-1.04	-1.37
Property Variables	Yes		Yes		Yes		Yes	
Seller Variables	Yes		Yes		Yes		Yes	
Closing Year-Quarter FE	Yes		Yes		Yes		Yes	
Census Tract FEs	Yes		Yes		Yes		Yes	
Adj R ²	0.19		0.20		0.18		0.20	
Obs.	4,940		33,082		6,715		1,666	

Note: This table reports the estimation results of equation on Abs(Price Spread) or APS by housing type. Variables are defined in Table 1. CBG level locational fixed effects are controlled. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels of confidence, respectively.

[Insert Table 4 here]

5.3 Variations across Time

Our Google trend analysis (Fig. 1) suggests that the use of Zillow by households increased prior to 2015 and plateaued thereafter. This may indicate that prior to 2015, fewer households were familiar with Zillow and used it to gather information on properties, while between 2015 and 2018 Zillow was established as a source of information regularly used by most households.

To assess whether our results for *Online Estimate* and *Photo Count* differ between 2011 to 2014 and 2015 to 2018, which may represent an explanation for our findings for semi-detached homes in Table 4, we separate our sample into two sub-samples based on these time periods and estimate our model in Eq. 1 for each sub-sample and

housing type. Our results are presented in Table 5a for condos and townhomes and Table 5b for detached and semi-detached single-family homes.

Table 5
a: Results for APS (Matched Sample) Separated by Time Period

	Condo					Townhome						
	2011–2014			2015–2018		2011–2014			2015–2018			
	Coef		t-stat	Coef		t-stat	Coef		t-stat	Coef		t-stat
Online Estimate	-0.10		-0.40	0.03		0.22	-0.47 *		-1.80	-0.48 **		-2.25
Photo Count	-0.02		-1.61	-0.03 ***		-3.86	-0.11 ***		-11.49	-0.07 ***		-12.88
Log(Trans. Vol _{cbg})	-0.37		-1.47	-0.18		-0.95	0.13		0.76	-0.10		-0.88
Log(TOM)	0.41 ***		4.77	0.51 ***		10.14	0.39 ***		6.73	0.36 ***		11.59
Close Price	-0.004 **		-2.47	-0.004 ***		-5.22	-0.03 ***		-19.28	-0.02 ***		-27.70
Agent Owned	0.15		0.20	0.42		0.91	-1.26 ***		-3.06	-0.25		-1.16
Property Variables	Yes			Yes			Yes			Yes		
Seller Variables	Yes			Yes			Yes			Yes		
Closing Year-Quarter FE	Yes			Yes			Yes			Yes		
CBG FEs	Yes			Yes			Yes			Yes		
Adj R ²	0.23			0.14			0.23			0.18		
Obs.	1,666			3,274			9,914			23,168		
Note: This table reports the estimation results of equation on Abs(Price Spread) or APS by housing type. Variables are defined in Table 1. CBG level locational fixed effects are controlled. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels of confidence, respectively.												

Table 5
b: Results for APS (Matched Sample) Separated by Time Period

	Semi-Detached					Detached Single-Family						
	2011–2014		2015–2018			2011–2014		2015–2018				
	Coef	t-stat	Coef	t-stat		Coef	t-stat	Coef	t-stat			
Online Estimate	-0.09	-0.26	-1.18	**	-2.01	-0.43	-0.71	-1.52	**	-2.50		
Photo Count	-0.01	-1.01	-0.04	***	-3.44	-0.07	**	-2.47	-0.04	-1.60		
Log(Trans. Vol _{cbg})	0.33	1.49	0.18		0.68	-0.26	-0.53	-0.12		-0.27		
Log(TOM)	0.33	***	4.26	0.33	***	4.63	0.25	1.58	0.38	***	3.08	
Close Price	-0.07	***	-19.38	-0.04	***	-14.91	-0.02	***	-3.68	-0.02	***	-6.43
Agent Owned	-0.11	-0.20	1.35	**	2.38	-0.22	-0.19	-2.22	**	-2.08		
Property Variables	Yes		Yes			Yes		Yes				
Seller Variables	Yes		Yes			Yes		Yes				
Closing Year-Quarter FE	Yes		Yes			Yes		Yes				
CBG FEs	Yes		Yes			Yes		Yes				
Adj R ²	0.25		0.18			0.16		0.20				
Obs.	2,689		4,026			675		991				
Note: This table reports the estimation results of equation on Abs(Price Spread) or APS by housing type. Variables are defined in Table 1. CBG level locational fixed effects are controlled. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels of confidence, respectively.												

As shown in Table 5a, *Online Estimate* continues to have no effect on the price spread for condos, irrespective of time period. The number of photos associated with a condo had no relationship in the early period but significantly reduces the price spread in the later period. This may result from more agents sharing more photos for condos knowing that households are more likely to view them, for example, on platforms such as Zillow. Our results for townhomes in Table 5 are in line with Table 4. Irrespective of period, free online value estimates and photos negatively affect price spread. Interestingly, the coefficient on *Online Estimate* is only significant at the 10% level in the 2011 to 2014 period but significant at the 1% level in the 2015 to 2018 period.

[Insert Table 5a here]

The results for semi-detached homes in Table 5b suggest that *Online Estimate* has no relationship with the price spread in the 2011 to 2014 period. However, it has a consistently negative relationship with the price spread in later period. This suggests that our findings for semi-detached homes in Table 4 were influenced by the aggregation of

the two time periods. Interestingly, the number of photos associated with a semi-detached property only reduces the price spread in the 2015 to 2018 period, but not before. The explanation for this finding may be the same as for condos.

Free Zestimate information has no relationship with the price spread for detached single-family homes in the 2011 to 2014 period, but a significantly negative one in the 2015 to 2018 period. One explanation for this finding is that households buying these types of homes relied less on information on Zillow in the earlier period. Another is that the precision of AVM and quality of Zestimates increased over time, which may have resulted in a higher value to households interested in purchasing a detached single-family home in the later period. This in turn may explain the change in explanatory power of *Online Estimate* for the price spread for this housing type. The results suggest that our findings for *Online Estimate* for this housing type in Table 4 were driven by the 2015 to 2018 period.

While the coefficient on *Photo Count* for detached single-family in Table 6 is significant in the 2011 to 2014 period, it is insignificant for the 2015 to 2018 period. Thus, the number of photos associated with a detached single-family home has no economically significant impact on the price spread for this housing type. One explanation is that residential agents established a practice of providing as many photos as possible for a detached single-family home in the latter period, which results in limited variation in this variable. Overall, our results in Table 5a and 5b are in line with Table 4 and provide evidence that free online information, either in form of photos or Zestimates, reduces the price spread for more heterogeneous housing types, particularly after 2015.

[Insert Table 5b here]

6. Conclusion

The relationships of households with financial advisors or residential real estate agents are characterized by information asymmetries, which affect the advisor's behavior and recommendations as well as outcomes for clients. Using the housing market as a laboratory, we investigate whether free online information such as Zillow's value estimate and the number of photos associated with a residential property reduce information asymmetries between clients and agents. To capture information asymmetries, we create a price spread between list and sales price of a property, which conceptually aligns with the bid-ask spread for in other financial markets.

We first hypothesize that the availability of a Zestimate and number of photos reduce the price spread. Second, we hypothesize that the impact of free online information on reducing information asymmetries is larger for more heterogeneous housing types such as townhomes, semi-detached and detached single-family homes. For these housing type, free online information improves the information environment for households. On the other hand, condos are more homogeneous, and free online information is expected to have less informative value to households.

Using a sample of 62,171 transactions for Philadelphia over the period of 2011 to 2018, we find that, compared to properties without a Zestimate, the availability of a free value estimate reduces the price spread for more heterogeneous housing types such as townhomes, semi-detached and detached houses. On the other hand, it has no impact on the price spread for condos. The number of available photos has a negative relationship with the price spread for all housing types with the exception of detached single-family in 2015–2018 period. The results for the latter period of detached single-family may be explained by the practice of listing agents to generally provide a lot of photos for detached houses. Additional analyses suggest that our findings for condos, semi-

detached and detached houses are driven by the 2015 to 2018 period during which Zillow was well-established as a source of information for the general public. Our results for townhomes are robust to different time periods.

We consider our study relevant not only to housing markets, but also other areas such as insurance or financial planning due to the similarities of client-advisor relationships (Smith et al., 2019; Bolton et al., 2007). Our study represents the starting point to further investigations into the informative value of free online information, particularly in the context of information asymmetries and principal-agent relationships. Future studies with the appropriate datasets may complement our study by investigating how free stock market or other financial information driven by FinTech innovations affects the reliance of households on financial advisors, investment behavior, information asymmetries and principal-agency issues. Additionally, with the rise of artificial intelligence (AI), future studies may investigate how the reliance of AI for financial advice affects information asymmetries, the relationship of households and financial advisers as well as the performance of investment decisions made by AI.

Declarations

Author Contribution

Youngme Seo: Conceptualization, Investigation, Data Curation, Literature Review. Dongshin Kim: Methodology, Formal Analysis, Validation, Interpretation of Results. Julia Freybote: Literature Review, Writing – Original Draft, Writing – Review & Editing, Manuscript Organization.

References

1. Allen, M. T., Cadena, A., Rutherford, J., & Rutherford, R. C. (2015). Effects of Real Estate Brokers' Marketing Strategies: Public Open Houses, Broker Open Houses, MLS Virtual Tours, and MLS Photographs. *Journal of Real Estate Research*, 37(3), 343–369. <https://doi.org/10.1080/10835547.2015.12091422>
2. Anglin, P. M., & Arnott, R. (1991). Residential real estate brokerage as a principal-agent problem. *Journal of Real Estate Finance and Economics*, 4, 99–125. <https://doi.org/10.1007/BF00173119>
3. Bai, Z., Zheng, S., & Hu, J. (2025). Is Social Media the New Retirement Advisor? Assessing the Impact of Social Media Influence on Retirement Planning. *Journal of Consumer Affairs*, 59, e70005. 10.1111/joca.70005. <https://onlinelibrary.wiley.com/doi/>
4. Bai, J., Shang, C., Wan, C., & Zhao, Y. E. (2022). Social Capital and Individual Ethics: Evidence from Financial Adviser Misconduct. *Journal of Business Ethics*, 181, 495–518. <https://doi.org/10.1007/s10551-021-04910-4>
5. Barbon, A., Di Maggio, M., Franzoni, F., & Landier, A. (2019). Brokers and Order Flow Leakage: Evidence from Fire Sales. *Journal of Finance*, 74(6), 2707–2749. 10.1111/jofi.12840
6. Benefield, J. D., Cain, C. L., & Johnson, K. H. (2011). On the Relationship Between Property Price, Time-on-Market, and Photo Depictions in a Multiple Listing Service. *Journal of Real Estate Finance and Economics*, 43, 401–422. <https://doi.org/10.1007/s11146-009-9219-6>
7. Benjamin, J. D., & Chinloy, P. T. (2000). Pricing, Exposure and Residential Listing Strategies. *Journal of Real Estate Research*, 20(1/2), 61–74. <https://doi.org/10.1080/10835547.2000.12091026>

8. Bergstresser, D., Chalmers, J. M. R., & Tufano, P. (2009). Assessing the Costs and Benefits of Brokers in the Mutual Fund Industry. *Review of Financial Studies*, 22(10), 4129–4156. 10.1093/rfs/hhp022
9. Bhattacharya, U., Kumar, A., Visaria, S., & Zhao, J. (2024). Do Women Receive Worse Financial Advice? *Journal of Finance*, 79(5), 3261–3308. 10.1111/jofi.13366
10. Bian, X., Turnbull, G. K., & Waller, B. D. (2017). Client Externality Effects of Agents Selling Their Own Properties. *Journal of Real Estate Finance and Economics*, 54, 139–164. 10.1007/s11146-015-9543-y
11. Bigel, K. S. (2000). The Ethical Orientation of Financial Planners Who ARE Engaged in Investment Activities: A Comparison of United States Practitioners Based on Professionalization and Compensation Sources. *Journal of Business Ethics*, 28, 323–337. <https://doi.org/10.1023/A:1006258813653>
12. Bolton, P., Freixas, X., & Shapiro, J. (2007). Conflicts of interest, information provision, and competition in the financial services industry. *Journal of Financial Economics*, 52, 297–330. 10.1016/j.jfineco.2005.06.004
13. Calcagno, R., & Monticone, C. (2015). Financial literacy and the demand for financial advice. *Journal of Banking & Finance*, 50, 363–380. <https://doi.org/10.1016/j.jbankfin.2014.03.013>
14. Callahan, C. M., Lee, C. M. C., & Yohn, T. L. (1997). Accounting Information and Bid-Ask Spreads. *Accounting Horizons*, 11(4), 50–60.
15. Chen, H., De, P., Hu, Y., & Hwang, B. H. (2014). Wisdom of Crowds: The Value of Stock Opinions Transmitted Through Social Media. *Review of Financial Studies*, 27(5), 1367–1403. <https://www.jstor.org/stable/24465404>
16. Cookson, J. A., Lu, R., Mullins, W., & Niessner, M. (2024). The Social Signal. *Journal of Financial Economics*, 158, 103870. <https://doi.org/10.1016/j.jfineco.2024.103870>
17. Cookson, J. A., & Niessner, M. (2020). Why Don't We Agree? Evidence from a Social Network of Investors. *Journal of Finance*, 75(1), 173–228. 10.1111/jofi.12852
18. Copeland, T. E., & Galai, D. (1983). Information effects on the bid-ask spread. *Journal of Finance*, 38(5), 1457–1469. <https://doi.org/10.2307/2327580>
19. Christoffersen, S. E. K., Evans, R., & Musto, D. K. (2013). What do Consumers' Fund Flows Maximize? Evidence from Their Brokers' Incentives. *Journal of Finance*, 68(1), 201–235. <https://www.jstor.org/stable/23324395>
20. Clauretie, T. M., & Daneshvary, N. (2008). Principal-Agent Conflict and Broker Effort Near Listing Contract Expiration: The Case of Residential Properties. *Journal of Real Estate Finance and Economics*, 37, 147–161. <https://doi.org/10.1007/s11146-007-9045-7>
21. D'Astous, P., Gemmo, I., & Michaud, P. C. (2024). The quality of financial advice: What influences recommendations to clients? *Journal of Banking & Finance*, 169, 107291. <https://doi.org/10.1016/j.jbankfin.2024.107291>
22. Demsetz, H. (1968). The cost of transacting. *The quarterly journal of economics*, 82(1), 33–53.
23. Diamond, D. W., & Verrecchia, R. E. (1991). Disclosure, liquidity, and the cost of capital. *Journal of Finance*, 46(4), 1325–1359. <https://doi.org/10.1111/j.1540-6261.1991.tb04620.x>
24. Dimmock, S. G., Gerken, W. C., & Van Alfen, T. (2021). Real Estate Shocks and Financial Advisor Misconduct. *Journal of Finance*, 76(6), 3309–3346. 10.1111/jofi.13067
25. Dimmock, S. G., Gerken, W. C., & Graham, N. P. (2018). Is Fraud Contagious? Coworker Influence on Misconduct by Financial Advisors. *Journal of Finance*, 73(3), 1417–1450. 10.1111/jofi.12613
26. Egan, M., Matvos, G., & Seru, A. (2019). The Market for Financial Adviser Misconduct. *Journal of Political Economy*, 127(1), 233–295. <https://doi.org/10.1086/700735>

27. Eliner, L., & Kobilov, B. (2023). To the Moon or Bust: Do Retail Investors Profit from Social Media-Induced Trading? Working paper. <https://afajof.org/management/viewp.php?n=64120>
28. Feng, J., Jiao, W., & Wang, Y. (2025). Bank fintech and lending distance: The role of information asymmetry and risk management channels. *Economic Modelling*, 151, 107154. <https://doi.org/10.1016/j.econmod.2025.107154>
29. Foerster, S., Linnainmaa, J. T., Melzer, B. T., & Previtero, A. (2017). Retail Financial Advice: Does One Size Fit All? *Journal of Finance*, 72(4), 1441–1482. 10.1111/jofi.12514
30. Glosten, L. R., & Milgrom, P. R. (1985). Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics*, 14(1), 71–100. [https://doi.org/10.1016/0304-405X\(85\)90044-3](https://doi.org/10.1016/0304-405X(85)90044-3)
31. Glower, M., Haurin, D. R., & Hendershott, P. H. (1998). Selling time and selling price: The influence of seller motivation. *Real Estate Economics*, 26(4), 719–740. <https://doi.org/10.1111/1540-6229.00763>
32. Gomez, E. A. (2024). The Effect of Mandatory Disclosure Dissemination on Information Asymmetry among Investors: Evidence from the Implementation of the EDGAR System. *The Accounting Review*, 99(1), 235–257. 10.2308/TAR-2020-0602
33. Greenstein, M. M., & Sami, H. (1994). The Impact of the SEC's Segment Disclosure Requirement on Bid-Ask Spreads. *The Accounting Review*, 69(1), 179–199. <https://www.jstor.org/stable/248266>
34. Gwin, C. R., Ong, S. E., & Gwin, C. F. (2002). Seller versus Broker: Timing of Promotion. *Journal of Real Estate Research*, 24(1), 27–45. <https://doi.org/10.1080/10835547.2002.12091085>
35. Hackethal, A., Haliassos, M., & Jappelli, T. (2012). Financial advisors: A case of babysitters? *Journal of Banking & Finance*, 36(2), 509–524. <https://doi.org/10.1016/j.jbankfin.2011.08.008>
36. Hoechle, D., Ruenzi, S., Schaub, N., & Schmid, M. (2018). Financial Advice and Bank Profits. *Review of Financial Studies*, 31(11), 4447–4492. 10.1093/rfs/hhy046
37. Hoechle, D., Ruenzi, S., Schaub, N., & Schmid, M. (2017). The Impact of Financial Advice on Trade Performance and Behavioral Biases. *Review of Finance*, 871–910. 10.1093/rof/rfw032
38. Jame, R., Johnston, R., Markov, S., & Wolfe, M. C. (2016). The Value of Crowdsourced Earnings Forecasts. *Journal of Accounting Research*, 54(4), 1077–1110. <https://www.jstor.org/stable/24738215>
39. Jeon, Y., Seiler, M. J., & Seo, Y. (2023). The Impact of Public Information on Housing Market Decisions: Evidence from Third-Party AVMs. *Journal of Real Estate Research*, 45(1), 83–110. <https://doi.org/10.1080/08965803.2022.2060905>
40. Jud, G. D., Winkler, D. T., & Kissling, G. E. (1995). Price spreads and residential housing market liquidity. *The Journal of Real Estate Finance and Economics*, 11, 251–260. <https://doi.org/10.1007/BF01099111>
41. Kling, L., König-Kersting, & Trautmann, S. T. (2023). Investment preferences and risk perception: Financial agents vs. clients. *Journal of Banking & Finance*, 154, 106489. <https://doi.org/10.1016/j.jbankfin.2022.106489>
42. Kurlat, P., & Stroebel, J. (2015). Testing for information asymmetries in real estate markets. *The Review of Financial Studies*, 28(8), 2429–2461. <https://doi.org/10.1093/rfs/hhv028>
43. Levitt, S. D., & Syverson, C. (2008). Market distortions when agents are better informed: The value of information in real estate transactions. *The Review of Economics and Statistics*, 90(4), 599–611. <https://www.jstor.org/stable/40043103>
44. Lin, Z., & Vandell, K. D. (2007). Illiquidity and pricing biases in the real estate market. *Real Estate Economics*, 35(3), 291–330. <https://doi.org/10.1111/j.1540-6229.2007.00191.x>

45. Liu, P., & Xie, J. (2021). Optimal Contract Design in Residential Brokerage. *Real Estate Economics*, 49(2), 493–530. 10.1111/1540-6229.12283
46. Luchtenberg, K. F., Seiler, M. J., & Sun, H. (2019). Listing Agent Signals: Does a Picture Paint a Thousand Words? *Journal of Real Estate Finance and Economics*, 59, 617–648. <https://doi.org/10.1007/s11146-018-9674-z>
47. Quigley, J. M. (2002). *Transactions costs and housing markets*. Wiley.
<https://doi.org/10.1002/9780470690680.ch4>
48. Rutherford, R. C., Springer, T. M., & Yavas, A. (2005). Conflicts between principals and agents: evidence from residential brokerage. *Journal of Financial Economics*, 76(3), 627–665.
<https://doi.org/10.1016/j.jfineco.2004.06.006>
49. Sankaraguruswamy, S., Shen, J., & Yamada (2013). The relationship between the frequency of news release and the information asymmetry: The role of uninformed trading. *Journal of Banking & Finance*, 37(11), 4134–4143. <https://doi.org/10.1016/j.jbankfin.2013.07.026>
50. Schmidt, D. (2020). Stock Market Rumors and Credibility. *Review of Financial Studies*, 33(8), 3804–3853.
<https://www.jstor.org/stable/10.2307/48587199>
51. Smith, P. S., Zahirovic-Herbert, V., & Gibler, K. M. (2019). Building Social Capital at the Expense of Principals: Evidence from Residential Real Estate Agent Trading Networks. *Journal of Real Estate Research*, 41(1).
<https://doi.org/10.1080/10835547.2019.12091519>
52. Turnbull, G. K., Waller, B. D., & Wentland (2022). Mitigating agency costs in the housing market. *Real Estate Economics*, 50, 829–861. 10.1111/1540-6229.12349
53. Wiley, J. A., & Zumpano, L. V. (2011). The Limited-Service Brokerage Decision: Theory and Evidence. *Journal of Real Estate Finance and Economics*, 43, 336–358. 10.1007/s11146-009-9217-8
54. Wong, S. K., Deng, K. K., & Chau, K. W. (2022). Do short-term real estate investors outperform the market? *Journal of Real Estate Research*, 44(2), 287–309. <https://doi.org/10.1080/08965803.2021.2008608>
55. Xie, J. (2018). Who is misleading whom in real estate transactions? *Real Estate Economics*, 46(3), 527–558.
<https://doi.org/10.1111/1540-6229.12196>
56. Zahirovic-Herbert, V., Waller, B. D., & Turnbull, G. K. (2020). Properties that Sell at or above Listing Price: Strategic Pricing, Better Broker or Just Dumb Luck? *Journal of Real Estate Finance and Economics*, 60, 53–76.
<https://doi.org/10.1007/s11146-019-09714-y>

Footnotes

1. Our focus on Zillow as a source of free online information stems from the fact that it is the leading source of residential real estate information that households use compared to Realtor.com, Redfin or others. Zillow draws internet traffic that is comparable to Reddit or Netflix. For example, in the first quarter of 2025, it had 227 million unique monthly users and approximately 160 million homes in their database.
<https://www.zillow.com/how-much-is-my-home-worth/>; <https://www.zillow.com/z/zestimate/>
2. <https://www.businessofapps.com/data/zillow-statistics/>

Figures

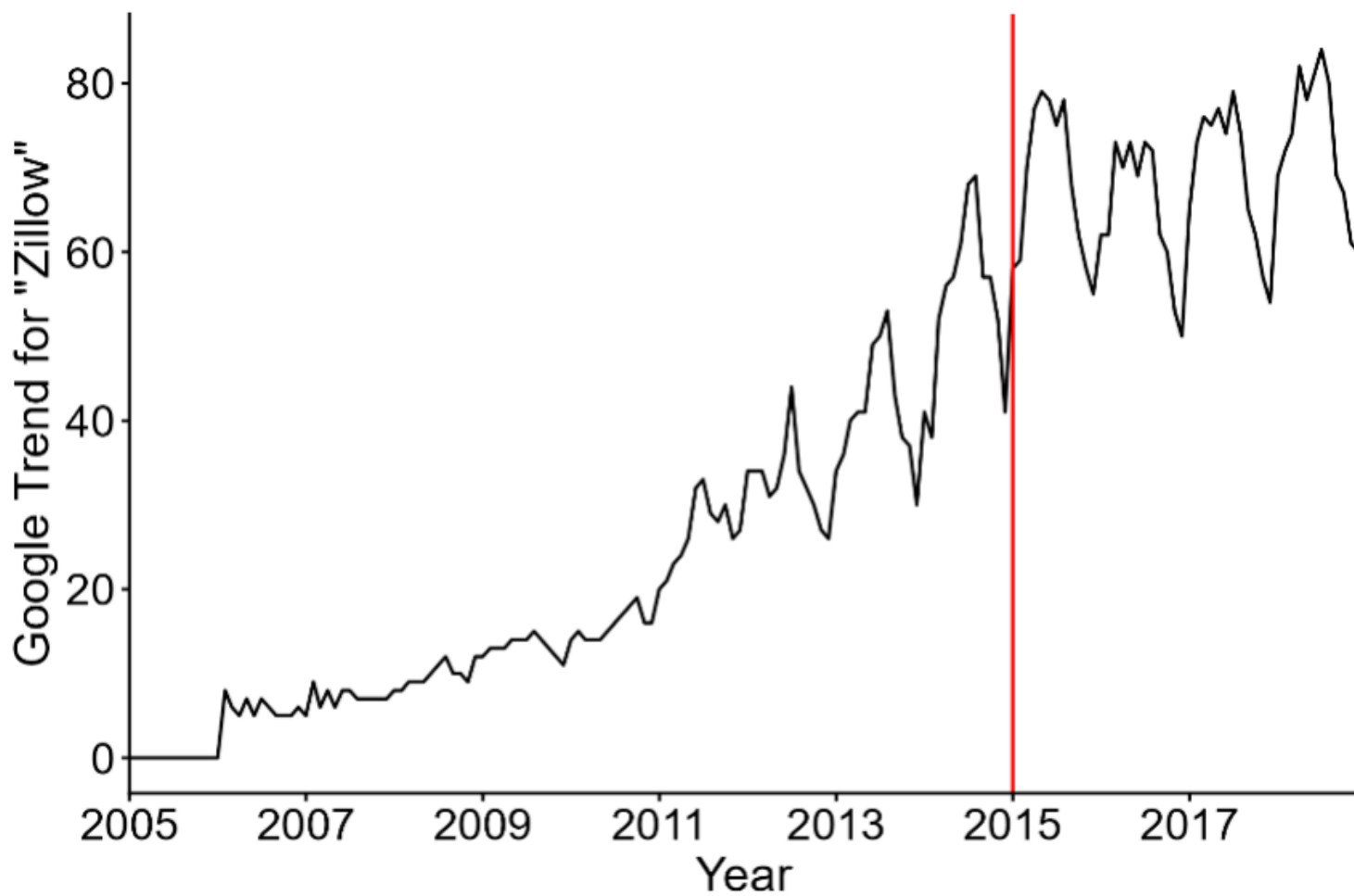


Figure 1

Google Trend Analysis for "Zillow"

Note: This figure displays Google trend on "Zillow" search in Philadelphia, PA over the period of 2005 to 2018.

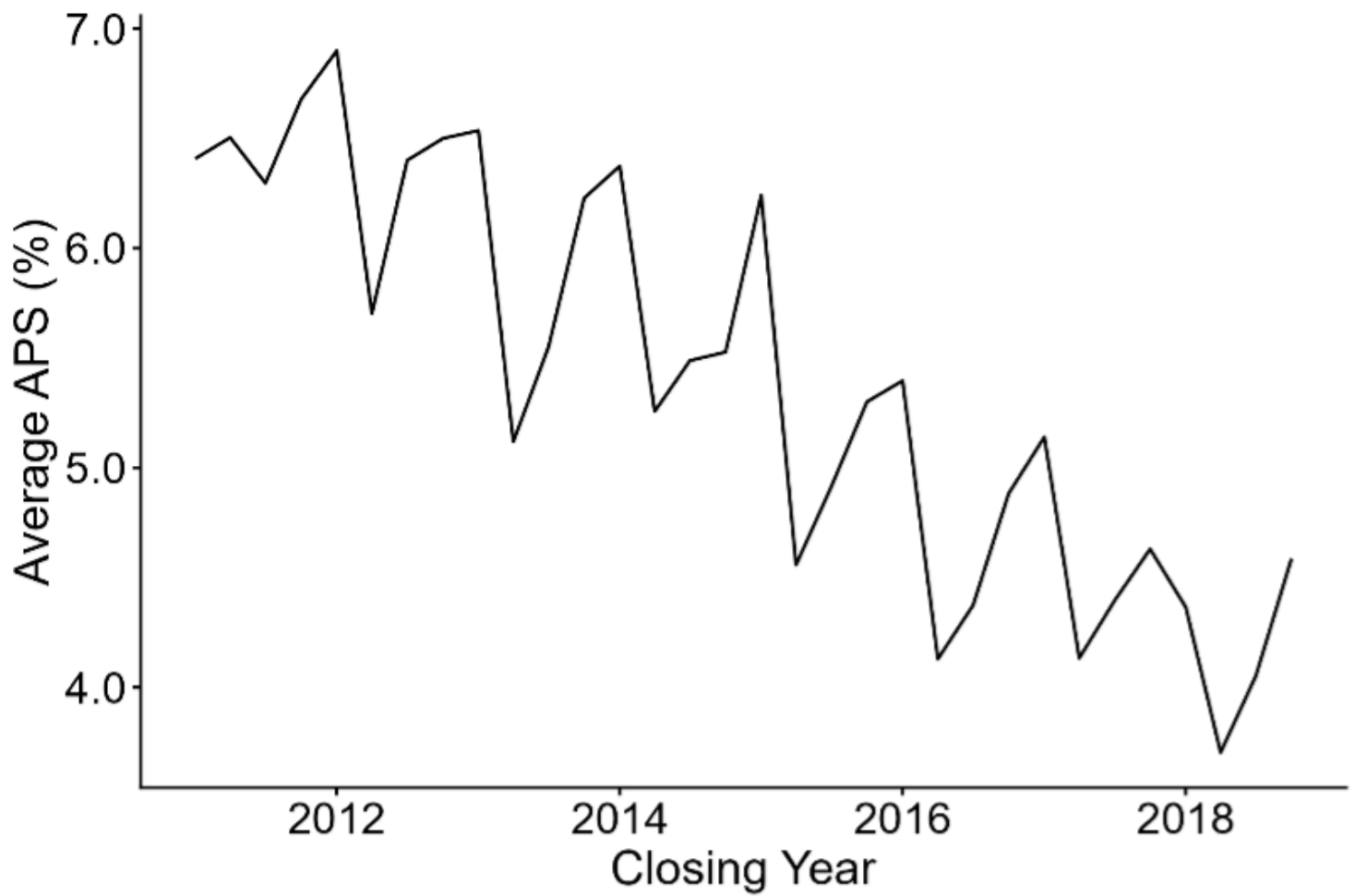


Figure 2

Absolute Value of Price Spread Over Time

Note: This figure displays the quarterly average APS. APS is the absolute value of Price Spread, where Price Spread is $(List\ Price - Close\ Price)/List\ Price \times 100$.