Algorithm failures and consumers' response: Evidence from Zillow

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Abstract

In November 2021, Zillow announced the closure of its iBuyer business. Popular media largely attributed this to a failure of its proprietary forecasting algorithm. We study the response of consumers to Zillow's iBuyer business closure. We show that after the iBuyer business closure, home sellers started making list-pricing decisions that deviated more from the Zestimate, Zillow's algorithmically generated estimate of a home's current value, suggesting that the iBuyer forecasting algorithm failure negatively affected consumer trust in the Zestimate algorithm. Moreover, sellers deviated more by increasing rather than decreasing their list price. We next look at the downstream consequences of the Zillow iBuyer closure on sales outcomes, such as sales price premium over the list price and time on the market. We find that properties are sold for more and in less time, both benefitting home sellers.

1 Introduction

Today, firms, organizations, and governments use algorithms to support decision-making through recommendations, classification, predictions, or forecasts. Consumers are continuously exposed to algorithmic decisions across different domains. For example, consumers observe algorithmic recommendations when they buy products from online marketplaces (e.g., Amazon), when they buy food (e.g., DoorDash, Uber Eats), or when they watch a movie (e.g., Netflix); and they are exposed to algorithmic predictions or forecasting when making financial decisions (e.g., Wealthfront, Betterment) or when buying and selling real estate properties (e.g., Redfin, Zillow).

The excitement around algorithms and artificial intelligence (AI) is big because of the benefits they promise. Algorithms are less prone to error than humans; they can easily scale and therefore reduce costs and improve performance (Brynjolfsson and McElheran 2019); and they can improve the quality and precision of decisions because they can take large amounts of data as input. Finally, recent research shows that algorithms can improve productivity (Bai et al. 2022).

Even in contexts where algorithms outperform humans or at least add value to human decision-making, their adoption may not be straightforward. A recent stream of research that studies the psychological aspects related to how consumers respond to AI's deployment suggests that consumers may not always follow algorithmic decisions, a phenomenon known as *algorithm aversion* (Dietvorst et al. 2015). Dietvorst and Bharti (2020), for example, find that people are less likely to use the best possible algorithm in decision domains that are more unpredictable (e.g., medical decision-making). Glaeser et al. (2021) find that, in the context of restaurant inspections, decision-makers are only half as likely to follow algorithmic recommendations compared to their own judgment.

In addition to the issue of algorithm aversion, researchers have started documenting how consumers react or respond to algorithm failures. Longoni et al. (2022), for example, show that algorithmic failures in government-related decisions are generalized more broadly than human failures, an effect the authors call *algorithmic transference*. Algorithmic transference is the phenomenon wherein a failure of one AI algorithm is transferred to another algorithm to a greater extent than a failure of a person is transferred to another person. Given the large investments in algorithms and AI across many domains, this literature, despite being in its infancy, raises important concerns about algorithm adoption and the potentially negative consequences of algorithm failures.

We add to this literature by empirically studying how consumers respond to algorithm failure in the context of the housing market. Our research uses data from Zillow, a popular online real estate platform that provides data on over 110 million homes across the US. We focus on two key algorithms used by Zillow. The first is a machine learning-based algorithmic estimate (called the Zestimate) of the current sales price value of every home on the platform. Home sellers and real estate agents alike use these estimates (among other sources of information) to decide at which price point to list a house for sale. Indeed, recent research suggests that Zillow's Zestimate affects both the list price (i.e., the price at which a home is listed for sale) and, in turn, the final sales price (i.e., the price at which the home sells for) (Fu et al. 2022, 2023, Malik and Manzoor 2020, Yu 2020). The second algorithm is used by Zillow in its iBuyer business through which Zillow would buy homes with minimal or no home inspection and resell them after making upgrades, ideally for a profit. Therefore, this algorithm helps the iBuyer business to forecast the sales price of an upgraded home a few months into the future.[1]

Zillow continues providing the Zestimates on its platform, with a nationwide median error rate for on-market homes of 2.4%. However, Zillow abandoned its iBuyer business in November 2021, mainly because the homes bought in the iBuyer business could not be sold in a timely manner at the profitable forecasted prices. Indeed, in the third quarter of 2021, the

[1] We refer to Zillow's Zestimate and iBuyer forecasting algorithms as two separate algorithms because they are used for different tasks, i.e., predicting real-time house prices and forecasting house prices. While Zillow does not disclose the specifics of any of the algorithms it uses, it is possible that they rely on similar methods (e.g., neural networks) and data (e.g., house characteristics and recent market trends). Nonetheless, algorithmic transference relies on consumer perceptions of algorithms being similar but not the same, not on the technical differences between them.

average gross loss per home sold was $80,771. Quoting Zillow's CEO: "We've determined the unpredictability in forecasting home prices far exceeds what we anticipated and continuing to scale Zillow Offers would result in too much earnings and balance-sheet volatility."[2] Most of the US popular press covered the news, discussing how Zillow's algorithms failed to accurately forecast home prices, leading Zillow to abandon the program.

We exploit the Zillow iBuyer business closure event to study consumers' response to algorithmic failures. If algorithmic transference is at play, we should expect home sellers to reduce their trust in Zillow's Zestimate. Since the Zestimate is used to make list price decisions, this reduced trust could affect the price point at which home sellers list their properties for sale. Further, by affecting consumer behavior, the iBuyer business closure could have indirect consequences on housing market outcomes such as final sales prices and time on market; that is, how long a property stays on the market before being sold.[3]

What would a decrease in trust in Zillow's Zestimate do to list prices? First, we consider how home sellers' pricing will deviate from the Zestimate after their trust in the Zestimate decreases. It is plausible that home sellers construct a posterior estimate (of home value or equivalently offers they will receive from buyers) by taking a weighted average of the Zestimate and their prior private estimation (Dietvorst et al. 2018, Balakrishnan et al. 2022).[4] When consumers trust Zillow's Zestimate, more weight is likely put on the Zestimate, leading to a posterior estimate that deviates less from the Zestimate. When consumers' trust in the Zestimate decreases, less weight is put on the Zestimate, leading to posterior estimates that are farther away from the Zestimate. We do not observe home sellers' posterior (or prior) estimates directly, but we observe their list price choices, which directly depend on home

[2]See: `https://www.cnn.com/2021/11/02/homes/zillow-exit-ibuying-home-business/index.html`

[3]It is worth noting that the Zillow iBuyer business was only active in a handful of housing markets. Altogether, the four major iBuyers platforms—Zillow, Opendoor, Offerpad, and Redfin—purchased only 1% of all US homes in 2021. Therefore, in most housing markets, we do not expect the Zillow iBuyer business to impact housing market outcomes directly.

[4]If home sellers never placed any weight on the Zestimate, we should see no impact of the iBuyer business closure.

sellers' estimates. Therefore, we expect an increased absolute deviation (both positive and negative) of observed list prices from Zestimate.

Second, we consider in which direction home sellers will be more likely to deviate; that is, by systematically increasing or decreasing their list prices after the trust in the Zestimate decreases. On the one hand, home sellers could decrease their list prices because they assume that, similar to the iBuyer forecasted prices, Zestimates are, on average, too high. On the other hand, reduced trust in the Zestimate should increase uncertainty about home values because sellers rely on one less source of information for their list price decision, which may lead to higher list prices. This follows from Lazear (1986), who proposes a model of pricing under demand uncertainty to explain retail pricing choices for "one-of-a-kind" products; that is, products that are sold infrequently and for which no two products are exactly similar (home sales is one example). In this model, home sellers will choose a high initial list price to learn the demand for their home and subsequently cut prices if the initial price is too high.

We start our analysis by estimating the impact of the iBuyer business closure on the absolute list price deviation from the Zestimate. To estimate the causal impact of the iBuyer business closure on absolute list price deviation, we rely on a strategy akin to difference-in-differences (DD) design that compares changes in list price deviation before and after the iBuyer business closure (first difference) with respect to a baseline of changes over the same months in the year prior to the iBuyer business closure (second difference).[5] Using this identification strategy, we find that list prices start to deviate more from the Zestimate after the iBuyer business closure, consistent with the role of algorithmic transference in reducing trust in the Zestimate. We next investigate whether, on average, consumers deviate above or below the Zestimate. We find that consumers set list prices higher than what Zillow recommends. This finding is consistent with Lazear's (1986) model of pricing under demand uncertainty for "one-of-a-kind" products.

[5]Liaukonytė et al. (2022) and Sim et al. (2022) use a similar strategy to estimate the impact of boycotts on brand sales and the impact of the COVID-19 pandemic on music consumption, respectively.

We complement these analyses with a battery of robustness checks aimed at reinforcing the causal interpretation of our results. In particular, we show that our results are robust to accounting for changes in housing market conditions, changes in Zillow's algorithm accuracy, changes in housing stock composition, and listing agent characteristics.

Having established that algorithmic transference is at play and that home sellers respond to the iBuyer business closure by listing properties at prices that deviate more and above the Zestimate, we move to study the consequences that this response may have on sales outcomes. In particular, we focus on three outcomes that can be affected by the consumer response we observe: (1) the sales price deviation with respect to Zestimate, (2) the sales price premium with respect to the list price, and (3) the time on market, measured as the number of days a property stays listed on the market before selling.

We start by showing that, on average, deviating above the Zestimate is correlated with (a) increased sales premium over the Zestimate, (b) decreased sales premium over the list price, and (c) increased time on market. Results (a) and (c) suggest that the iBuyer business closure, by increasing list price deviations, should lead to higher sales prices but a longer time on the market. However, unlike the initial list price, which is determined solely by the seller, the sales price and time on market are jointly determined by buyer-seller pricing, search, and bargaining decisions, and since it is likely that the iBuyer business closure not only impacts sellers' uncertainty but also buyers' uncertainty, the effect of the iBuyer business closure on sales outcomes is not clear a priori.[6] Consistent with correlation (a), we find that the iBuyer business closure is associated with a higher premium over the Zestimate. However, in contrast with correlations (b) and (c), we find that the iBuyer business closure is associated with a larger premium over the list price and a shorter time on the market. These results suggest that other effects beyond those generated by sellers' higher uncertainty are at play, and these effects lead to higher premiums over list prices and a lower time on

[6]While it would be interesting to study the effect of the iBuyer business closure on buyers, our dataset does not allow us to do so as we do not observe the home buyers' consideration sets and decisions beyond the final sales price of a property. Therefore, this paper focuses on the effect of the iBuyer business closure on home sellers.

market. Further, these results suggest that, on average, home sellers benefited from the iBuyer business closure because properties are sold for more and in shorter times.

Overall, in this paper, we show that trust in algorithms can be undermined by the failure of other seemly related algorithms, leading consumers to behave differently when exposed to algorithmic decisions. Therefore firms, platforms, and organizations using AI to improve decisions should be careful when releasing algorithms and updates, making sure to reduce the likelihood of failures because these failures could affect the use and adoption of other AI solutions.

2 Related literature

Our research relates to the literature on human interactions with algorithms. Much of this literature focuses on understanding the drivers and barriers to adopting algorithms. Several survey-based studies have documented that people fail to use algorithms despite their better performance (Fildes and Goodwin 2007, Sanders and Manrodt 2003, Vrieze and Grove 2009). This phenomenon, known as algorithm aversion (Dietvorst et al. 2015), has been attributed to several factors, including people's beliefs that algorithms will inevitably err (Einhorn 1986), skepticism about algorithms' ability to perform well in subjective tasks (Castelo et al. 2019), skepticism about algorithms' ability to account for unique characteristics (Longoni et al. 2019), and complexity in implementing algorithmic suggestions (Luo et al. 2021, Sun et al. 2022). Research has also explored alternatives to mitigate algorithmic aversion, such as allowing users to intervene with the algorithmic outputs (Dietvorst et al. 2018), and to improve the often suboptimal outcomes from human-algorithm collaboration, such as providing users with more transparency about the algorithm (Balakrishnan et al. 2022). Related research has also studied consumer responses to algorithmic failures. For example, Srinivasan and Sarial-Abi (2021) show that consumers respond less negatively to a "brand-harm crisis" caused by errors made by algorithms rather than those by humans, and Longoni et al.

(2022) show that people generalize algorithmic failures more broadly than human failures, an inferential process the authors refer to as "algorithmic transference."

More closely related to our context, recent work has studied human-algorithm interactions in the housing market. In particular, most of this research has focused on publicly available algorithmic estimates of property value, such as Zillow's Zestimate or the Redfin Estimate. One consistent finding in this stream of literature is that these estimates affect both the list price (i.e., the price at which a home is listed for sale) and, in turn, the final sales price (i.e., the price at which the home sells). Moreover, Fu et al. (2023) shows that the availability of these algorithmic estimates of property value increases buyer and seller welfare by reducing uncertainty in beliefs about property values.

In this paper, we add to these different streams of literature by empirically studying how consumers respond to algorithm failure in the housing market context. In particular, and building upon the concepts of algorithmic transference, trust, and aversion, we examine whether perceptions about the failure of an algorithm (i.e., Zillow's iBuying algorithm to forecast future house prices) reduces consumers' reliance on a seemingly related algorithm (i.e., Zillow's algorithm to predict current house prices).

3 Effects of reduced trust

In this section, we build upon prior literature to discuss the possible consequences of home sellers reducing their trust in the Zestimate because of the iBuyer business closure and the associated failure in its price forecasting algorithm. First, we discuss the effect on the price at which the home is first listed for sale. This list price is unilaterally set by the home seller (along with their agent) and thus should clearly reveal the impact of reduced trust in the Zestimate. Second, we discuss the effects on sale outcomes (sales price and time on market).

First-order impact on list price The direct effect of iBuyer business closure news on list prices is a priori nontrivial. On the one hand, the news could have led consumers to believe that the iBuyer business closure was entirely due to Zillow buying properties for above-market prices because the forecasted home prices were too high. If this is the case, we should expect home sellers to list their properties for prices lower than their Zestimates. On the other hand, some home sellers may become aware of the iBuyer business and the model, which consists of buying homes low and selling them high. If home sellers focus on the "buying low" part, they may think that Zillow predicted house prices to be lower than they should be to allow Zillow to buy properties for low prices. If this is the case, we should expect home sellers to list their properties for prices higher than their Zestimates after the iBuyer business closure news.

Impact of demand uncertainty on list price Lazear (1986) proposed a model of pricing under demand uncertainty to explain retail pricing choices for "one-of-a-kind" products; thus, products that are sold infrequently and for which no two products are exactly similar. The home sellers' choice of the list price is one example of pricing choices for "one-of-a-kind" products. Following Lazear's (1986) model, the seller chooses a high initial list price to learn the demand for their home and subsequently cuts the list price. The initial list price is increasingly higher if the seller expects to learn more from observed demand or has more uncertainty about the demand (Knight 2002).[7] The subsequent list price cuts are also larger as the seller resolves demand uncertainty (Herrin et al. 2004). Sass (1988) tests Lazear's (1986) theory and finds that prices are more rigid for newer homes and homes sold recently that have superior price information. In our setting, the reduced trust in the Zestimate increases the sellers' demand (or price) uncertainty, and consequently, it could result in higher list prices and larger subsequent list price cuts.

[7] The sellers' choice to list high under demand uncertainty is bounded. A very high list price signals to the buyers that the seller has a very high reservation price and discourages them from making any offer or engaging in bargaining (Horowitz 1992). Since this limits learning about demand, the seller's increase of the list price is bounded.

Impact of home value uncertainty on list price A third channel through which the iBuyer business closure could affect list prices is due to the shock affecting buyers' trust in the Zestimate. Reduced buyers' trust in the Zestimate should increase their uncertainty about home values which, in turn, can increase the variance in the distribution of the offers they make. In this situation, Haurin et al. (2010) find that list prices are higher because home sellers want to take advantage of the greater variance by waiting for an overly optimistic buyer.

Effects on sales outcomes Changes in list prices should have downstream consequences on sales outcomes, such as time on market (TOM) and sales price.

We start by considering time on market. The literature has shown that the initial list price has an impact on time on market (Yavas and Yang 1995). In particular, a higher initial list price or a larger degree of overpricing (relative to the expected sales price) should slow buyer offers and therefore increase time on market (Anglin et al. 2003). However, the reduced trust in the Zestimate (which drives up the list prices) may also increase sellers' uncertainty about the market and distort their reservation prices, which in turn decreases the return to staying on the market for longer and would translate into shorter time on market (Anenberg 2016). Therefore, whether time on market increases or decreases depends on which force (higher list prices or lower returns for staying on the market) dominates.

Second, we consider sales prices. There are multiple forces at play that can affect sales prices, including time on market and list prices. The effects of longer (shorter) time on market are mixed. On the one hand, longer TOM can lead to a higher sales price because there is a higher probability of finding a buyer with a high reservation price (Knight 2002). On the other hand, longer TOM can lead to a lower sales price because the longer time on market may stigmatize homes (Taylor 1999). Turning to list prices, higher list prices should lead to higher sales prices; however, the premium over the list price may be lower. Therefore, a priori, it is not clear whether sales price should increase or decrease, and the effect will depend on which forces dominate.

To summarize, the predicted effects of the iBuyer business closure on list prices and sales outcomes are ambiguous, and their direction will depend on which one of the forces we discussed dominates. We, therefore, turn to discuss the data and the analysis we used to investigate the effect of the iBuyer business closure on these outcomes and to resolve these ambiguities.

4 Empirical context and data

4.1 Zillow and iBuyer

Zillow Zillow.com is one of the largest online real estate companies in the US. One of its main features is the home value estimates (Zestimates) generated by its proprietary machine learning algorithms for over 110 million homes across the US. Zestimates have been displayed on Zillow's website for free since its launch in 2006.

Each property has an individual webpage on Zillow. On a property page, there are three types of information related to the estimated home value generated by the machine learning algorithms: the Zestimate, Zestimate range, and Zestimate history (see Figure 1).[8] The Zestimate is the predicted sales price of the property in real time. We refer to this dynamic estimate as the "live Zestimate." The estimated sales range is the range in which the sales price is predicted to fall, which can be viewed as an indicator of the confidence that Zillow has in its own sales price estimate, wherein a smaller sales range indicates higher confidence. One important feature of the housing market is that the value of a property changes over time. To track past changes, Zillow provides information about the past estimates of a property value via the Zestimate history, which comprises the monthly Zestimate of the

[8]The Zestimate range is given by the high and low estimated market value at which Zillow values a home. The more information available about a property, the smaller the range, and the more accurate the Zestimate.

property value covering the full period in which Zillow tracked the specific property (for this measure, Zillow does not report the estimated sales range). Generally, the Zestimate history shows the past evolution of the Zestimate aggregated at the monthly level. However, in the case of major algorithm updates, Zillow would recalculate the Zestimate history to reflect its best estimate of past property values. In such cases, the values in Zestimate history may differ from the actual live Zestimates displayed to consumers in the past.

In Figure 1, we provide a screenshot of the three types of Zestimate-related information for a property for which data was collected on January 19, 2023. The live Zestimate, which reflects the property's value on January 19, 2023, is \$360,000 with a sales range of \$335,000–\$385,000. The Zestimate history graph displays the property's Zestimate in the past for about ten years. Hovering over the graph will show users the property's Zestimate at different points in time. For example, in July 2020, the property's Zestimate was \$374,600.

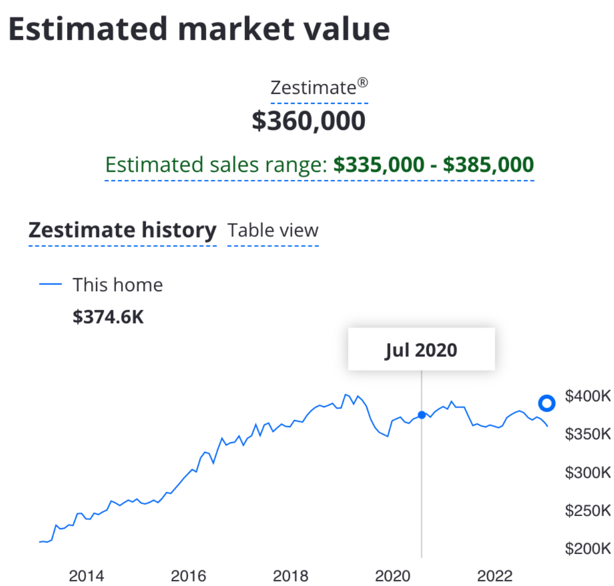

Figure 1: A screenshot of Zestimate-related information shown on a property page

iBuyer In addition to providing home value estimates, in 2018 Zillow launched its iBuyer business, a home-buying business program aimed at buying and reselling homes for a profit using a proprietary algorithm that forecasts home prices. The company started the iBuying program in Phoenix and Las Vegas, and by 2021, Zillow's iBuyer business operated in 25 cities across the country. Zillow was the second largest iBuyer business in the US (after Opendoor) until it decided to suspend the service at the beginning of November 2021. In a typical iBuyer transaction, an iBuyer makes an all-cash offer to the seller after minimal or no home inspection and does not request any repairs, warranties, closing costs, or commissions. Once purchased, the iBuyer invests in upgrading some home features and then lists the home for sale at a higher price. In theory, this new iBuyer role had two advantages for the market: (i) home sellers without the necessary funds or time to invest in costly repairs can monetize their homes, and (ii) the overall stock of homes on the market becomes renovated and up-to-date with the preferences of prospective residents. However, iBuyer also relies heavily on an accurate forecast of a home's sale value with upgraded home features and projections of the overall housing demand in a neighborhood. The reliance on the accuracy of algorithmic forecasts is a major risk for iBuying. And according to several media coverage and Zillow's reports, this was a primary factor in Zillow shutting down its iBuying business after reporting a loss of $328m in Q3 2021.[9]

4.2 Data collection

From Zillow, we collected a complete dataset of properties in Boston (MA) and Pittsburgh (PA). The full dataset consists of about 230,000 properties in Boston and about 250,000 properties in Pittsburgh. Note that Zillow's iBuyer business has never been available in these two cities; therefore, the iBuyer business (and its closure) should not have directly impacted the housing market in these two cities.

For each property, we collected all the information described in the previous section, including live Zestimate, Zestimate range, Zestimate history, price history, and property features. The information was repeatedly collected roughly every two weeks from February

[9]https://investors.zillowgroup.com/investors/news-and-events/news/news-details/2021/Zillow-Group-Reports-Third-Quarter-2021-Financial-Results--Shares-Plan-to-Wind-Down-Zillow-Offers-Operations/default.aspx

2019 to September 2022, excluding the period between October 2021 and December 2021 and the months of February, May, and June 2022 due to data collection issues . Therefore, we have multiple snapshots of the information available on Zillow for properties in Boston and Pittsburgh. In what follows, we describe how we construct the dataset for our analysis from this large full dataset. Using these snapshots and their value history, we can verify that Zillow did not make any substantial updates to its algorithm during the periods in which we have missing data. For the missing period between October and December 2021, we compare the Zestimate history data collected in January 2022 to that collected in September 2021. We find that in the common support (the period before September 2021), the two sets of Zestimate history data are identical, suggesting that there was no major algorithm update during the period for which we have no data. For February, May, and June 2022, we compare the Zestimate history of September 2022 with that of January 2022. Again, we find that in the common support (the period before January 2022), the two sets of Zestimate history data are identical, suggesting that there was no major algorithm update.

4.3 Data construction

For all the analyses reported in this paper, we focus on the 27,908 properties listed for sale between June 2019 and May 2022. For each property, we obtain its listing date, list price, selling date, and selling price from its sales price history.[10] Based on the listing date and the selling date, we calculate the time on market.

To study the effect of the iBuyer business closure on home sellers' trust in the Zestimate, we need to know the Zestimate value for each property when the property was listed on the market. To compute the Zestimates for properties listed for sale in month m, we take the Zestimate value from the Zestimate history of the first snapshot collected in month $m+1$. For example, to determine the Zestimate of a property listed for sale on May 25, 2019, we look at the Zestimate history of snapshot available in June 2019 and take the Zestimate

[10] A small number of properties were sold multiple times during our observation period; for these, we focus only on the first transaction.

value corresponding to May 2019 in the Zestimate history graph. Using Zestimate history data from the closer snapshot to the listing time alleviates concerns about potential major algorithm updates that could have happened between the listing time and the date of the snapshot collection and thus possibly affected the Zestimate history values. For the period for which our data collection failed, we rely on the Zestimate history of the next available snapshot.[11]

5 Empirical analysis

5.1 The impact of the iBuying business closure on list price deviation from the Zestimate

In this section, we estimate the causal impact of the iBuying program closure on list price deviation from the Zestimate. While the shock is likely exogenous and home sellers could not have anticipated or predicted Zillow's decision, performing a simple before and after analysis would likely lead to biased estimates. This is because doing so would not account for monthly shocks or seasonality effects in the real estate market that can impact list prices. To account for these shocks, and similar to Sim et al. (2022) and Liaukonytė et al. (2022), we rely on strategy akin to a difference-in-differences (DD) design by comparing changes in outcomes before and after the iBuyer business closure (first difference) and across years (second difference). Using this strategy, we estimate the impact of the iBuying business closure on list price deviation by comparing changes in list price deviation before and after the iBuying business closure with respect to a baseline of changes over the same months in the year prior to the iBuying business closure. Specifically, we define three one-year-long periods: (i) June 2019 to May 2020, (ii) June 2020 to May 2021, and (iii) June 2021 to May 2022. Since the buying program closure took place in November 2021, periods (i) and (ii) are

[11]As we discussed above, we did not observe any algorithm update during the period in which our data collection failed.

the controls, and (iii) is the treated period.[12] We then estimate the following specification:

$$\begin{aligned} \text{List price dev.}_{hzt} &= \beta_1 \text{ Treated}_{hz} + \beta_2 \text{ After}_t + \beta_3 \text{ After}_t \times \text{Treated}_{hz} \\ &+ \alpha_z + \tau_t + X'_{hzt}\delta + \epsilon_{hzt}, \end{aligned} \tag{1}$$

where the dependent variable is the absolute percentage deviation of the list price of house h in zipcode z with respect to its Zestimate at time of listing t (List price dev.$_{hzt}$ = |List Price$_{hzt}-$ Zestimate$_{hzt}$|/Zestimate$_{hzt}$). Treated$_{hz}$ indicates whether house h was listed in the treated period, and After$_t$ indicates whether the house was listed during or after the month of the iBuying business failure (November 2021). The specification includes zipcode fixed effects α_z to account for unobserved time-invariant location-specific confounders (e.g., houses in some areas might deviate more from its Zestimate), week-of-the-year fixed effects γ_t to control for time-varying shocks common to all properties, and a set of controls for house characteristics (e.g., bedrooms, bathrooms), X'_{hzt}. The coefficient of interest is β_3, which measures the differential list price deviation from the Zestimate after the iBuying business failure against a baseline of changes observed in previous years.

In addition to the treatment being exogenous, our identification strategy requires that the control periods represent a good counterfactual for the treated period, both before and after the treatment. In other words, in the absence of the treatment, list price deviation in the treated year would have evolved similarly to that of control years. While this assumption is untestable because we do not observe the counterfactual list price deviation had the iBuyer business closure not happened, a standard way to support this assumption is to check that the treated and controls group outcomes evolve similarly in the pre-treatment period. To test whether this is the case, we implement an event study design by estimating Equation 1 but replacing After$_t$ with a set of monthly leads and lags around the treatment time (November).

[12] The motivation behind the definition of these periods is twofold. First, Zillow announced a major algorithmic update in late April 2019; hence, the earlier data we can use as a control group is from June 2019. Second, defining the cycles from June to May of the following year allows us to have a fairly balanced number of months before and after the month of the treatment (November).

As is usual in this type of analysis, we set the baseline period to be the period just before the treatment begins (in our case, October). In Figure 2, we plot the estimated leads and lags with their respective 95% confidence intervals. Reassuringly, we observe that all pre-treatment estimates are close to zero, suggesting that the outcome evolved similarly for treated and control periods in that period. In addition, estimates become positive in the post-treatment period, suggesting that list price deviation increases more for the treated period compared to the control period after the iBuyer business closure.

Having established the validity of the assumptions behind our identification strategy, we proceed to estimate Equation 1. We report these estimates in Column 1 of Table 2. The coefficient of interest is positive and significant, suggesting that list price deviations from each house's Zestimate increased by 1 percentage point after the iBuying business closure. Considering a baseline deviation equal to the 4.26%, our results suggest that list prices deviate 23.47% more than before the iBuying business closure.[13] These results suggest that consumers responded to the iBuyer business closure by reducing their trust in Zillow's Zestimate and therefore started deviating more from Zillow's recommendations.

5.2 Do home sellers deviate more below or above their Zestimate values?

As we discussed in Section 3, whether home sellers will deviate by increasing or by decreasing list prices with respect to Zestimates is unclear because there are many forces at play.

To examine whether the failure of the iBuying business led home sellers to deviate above or below their respective Zestimate values, we continue to use Equation 1 but replace the absolute price deviation outcome with these three variables: (i) an indicator for whether the list price was above the Zestimate, (ii) an indicator for whether the list price was

[13]Given that the sign of our estimated treatment effect is positive, a baseline that includes the post-treatment observations is a conservative estimate of the magnitude of the treatment effect. Indeed, the average deviation in the pre-treatment period is 4.08 percentage points, suggesting that our estimated treatment effect translates into a 24.51% higher deviation than before the iBuying business closure.

below the Zestimate, and (iii) the non-absolute percentage deviation from the Zestimate (List price dev.$_{ht}$ = (List Price$_{ht}$ − Zestimate$_{ht}$)/Zestimate$_{ht}$). We report the results in Table 2. The estimates suggest that after the iBuying business closure, deviation above the Zestimate increased by 10.2% (Column 2), deviation below the Zestimate decreased by 15.1% (Column 3), and the non-absolute percentage deviation from the Zestimate increased by 1.4% (Column 4). These results suggest that home sellers are more likely to deviate above the Zestimate provided by Zillow, and are in line with the theory that home sellers may select a high initial list price to alleviate the increased uncertainty about the demand for their homes.

Before studying the downstream consequences of the consumer response we just documented, we discuss a set of robustness checks to reinforce the causal interpretation of our results.

6 Robustness checks

While home sellers could not have anticipated the iBuying program failure, this event could be correlated with other factors affecting home sellers' list price decisions. In this section, we discuss and rule out alternative explanations for the findings discussed in Section 5.

Changes in housing market conditions A potential concern with our analysis is that the iBuying program failure is correlated with changes in the housing market conditions. Such changes could directly influence how sellers make their pricing decisions. For example, sales prices increased steadily in 2021, which may have incentivized home sellers to increase their list prices. To address concerns regarding changing market conditions affecting our estimates, we control for month-to-month city-specific changes in the median sales price, number of new listings, median sales price to list price, and median days on market. In Column 1 of Table 3, we show that our main estimate of interest does not change substantially when we include these controls, suggesting that these factors are not driving our results.

Changes in Zestimate values Another concern is that after the iBuying business failure, Zillow lost confidence not only in its sales price forecasting algorithm but also in its estimates of current property values, which in turn also changed how much home sellers rely on Zestimates to make their pricing decisions. As mentioned in Section 4, we do not observe any major changes in the Zestimate values after the iBuying business failure. However, it is still possible that Zillow updated the Zestimate range to reflect higher uncertainty around its estimates (i.e., by displaying larger confidence intervals in the estimated sales price). If this is the case, our findings could reflect home sellers' reactions to changes in the confidence or certainty of the Zestimate rather than a reduced trust in the algorithm itself.

To address this concern, we add as an additional control the estimated Zestimate range that Zillow provides to home sellers. As discussed in Section 4.3, because of data collection issues, our dataset does not contain live Zestimate (and, thus, the Zestimate range) for the period between September 2021 to January 2022, and the months of February, March, and June 2022. To recover this variable for all months, we use the individual snapshots we collect every two weeks for each property. For the properties listed during this period, we approximate the estimated Zestimate range at the time of listing by linearly extrapolating Zestimate range values between two data points: (i) the Zestimate range we observe in the latest available snapshot of the property before it was listed for sale and (ii) the Zestimate range we observe in the earliest available snapshot after the property was listed for sale.[14] In Column 2 of Table 3, we show that the estimate of interest does not change substantially after controlling for this variable.

Listing agent size Another concern with our main finding relates to unobserved listing agent characteristics that could affect how much the sellers deviate the list prices from Zillow estimated house value. For instance, large real estate firms might have more resources to

[14]We also tested alternative approaches: one that uses the latest available value observed before the property was listed for sale and one that uses the earliest available value observed after the property was listed for sale. We report these estimates in Table 8 of Appendix A.1.

obtain more accurate estimates of a property value than small firms do. If the composition of sellers is affected by the iBuyer business closure, then our results could be biased.

To account for this possibility, we first identify whether a house is being sold by the owner or by a listing agent and then further categorize listing agents based on the quartiles of the number of listings they manage in our sample: (i) listing agents with 1 to 30 listings, (ii) listing agents with 30 to 100 listings, (iii) listing agents with 101 to 600 listings, and (iv) listing agents with 600+ listings. We then estimate Equation 1 and include these variables as a control. We report the estimates in Column 3 of Table 3. We observe that our results are not affected by including these controls.

Housing stock composition Another concern with our main finding relates to changes in housing stock composition correlated with the time of the iBuying business failure. Changes to the housing stock can affect our estimates in different ways. First, important changes in the composition of properties listed and sold could directly affect the Zestimate algorithm and, therefore, the predictions that Zillow makes, since these estimates consider the outcomes of properties with similar characteristics. Second, changes in housing stock could affect our estimates if some property characteristics are correlated with higher deviation from the Zestimate because they may be hard to price (e.g., single-family homes may have more unique amenities than condos and thus are harder to price than condos). If properties with these characteristics are more frequently listed after the iBuyer business closure, our estimates could be reflecting changes in housing composition rather than changes in consumer trust in Zillow's algorithm.

To reduce concerns about this issue, we show that the housing stock does not change substantially after the iBuyer business closure. To do so, we re-estimate Equation 1 on housing characteristics outcomes such as the number of bathrooms; number of bedrooms; the proportion of condos, townhouses, and single-family homes listed for sale; and the age of the house. We present these results in Table 4. Except for the number of bathrooms and the proportion of condos, which increase significantly but for which the estimates are close to zero (we observe 0.04 more bathrooms per house and 0.01 higher proportion of condos after the iBuyer business closure), the rest of the outcomes are not affected by the iBuyer business closure.

6.1 Sensitivity analyses

In this section, we test the sensitivity of our results to different controls and market definitions.

Different control groups First, we test the sensitivity of our results to different control periods. Specifically, we show that results hold when we compare the treated group (June 2021 to May 2022) only with the period June 2019 to May 2020 and only with the period June 2020 to May 2021. We report these results in Columns 1 and 2 of Table 5. We observe that our results are consistent when using different control periods.

Different markets Second, we test the sensitivity of our results to the two different markets used in our sample. Specifically, we show that our results hold when we separately analyze houses listed in the Pittsburgh (PA) and Boston (MA) markets. We report these results in Columns 3 and 4 of Table 5. We observe that our results are consistent across markets.

7 The downstream consequences of reduced trust in Zillow's Zestimate

So far, we have demonstrated that home sellers' response to the iBuyer business closure is to deviate more and above the Zestimate when making their list price decisions.

This section examines how list price deviations from Zestimates affect sale outcomes. In particular, we focus on three types of sale outcomes: (i) the sales price premium over the Zestimate observed at the time the property was listed for sale ((Sales price$_{ht}$ − Zestimate$_{ht}$)/ Zestimate$_{ht}$), (ii) the sales price premium over the list price ((Sales price$_{ht}$ − List Price$_{ht}$)/ List Price$_{ht}$), and (iii) the number of days the property stays on the market.

We start by estimating the overall impact of deviating from the Zestimate on sales outcomes. To do so, we estimate the following model over the set of homes sold during our observation period:

$$\text{Sale outcome}_{ht} = \beta \text{ List price dev.}_{ht} + \alpha_{zipcode} + \gamma_{week} + X_{ht}^{'}\delta + \epsilon_{ht}, \tag{2}$$

where Sale outcome$_{ht}$ is one of the three sale outcomes for house h listed at time t described above, and List price dev.$_{ht}$ is the percentage deviation of the list price with respect to its Zestimate at time of listing (List price dev.$_{ht}$ = (List Price$_{ht}$ − Zestimate$_{ht}$)/Zestimate$_{ht}$). As in Equation 1, the specification includes zipcode fixed effects $\alpha_{zipcode}$ to account for unobserved time-invariant location-specific confounders (e.g., houses in some areas might deviate more from their Zestimates), week-of-the-year fixed effects γ_{week} to control for time-varying shocks common to all properties, and a set of controls for house characteristics (e.g., bedrooms, bathrooms), $\mathrm{X}_{ht}^{'}$. The coefficient of interest is β, which measures the relationship between list price deviation from Zestimates and house sale outcomes.

We report the estimates of Equation 2 in Table 6. Our estimates suggest that, on average, a 1% deviation of the list price above its Zestimate is associated with a 0.77% higher sales price premium over its Zestimate (Column 1), a 0.16% lower sales price premium over the list price (Column 2), and 1.62% more days on the market (Column 3). These results point to a key trade-off for home sellers. By deviating more from the Zestimate when making list price decisions, home sellers can sell their properties for a higher price premium relative to their Zestimate, but these properties stay longer on the market and sell for a lower price premium relative to the list prices.

If the reduced trust in the Zestimate only affects home sellers, the results above could be used to predict the effect on sales outcomes of the iBuyer business closure since we showed that it leads to sellers deviating more from the Zestimate. Nonetheless, the reduced trust in the Zestimate could also affect buyers' uncertainty about home values, which, in turn, could affect the typical relationship between list price deviation from the Zestimates and sale outcomes. For instance, Anenberg (2016) suggests that higher buyer uncertainty discourages buyers from a lengthy search process, which could translate into a shorter time on market than usual. Thus, if these two forces are at play (sellers' and buyers' uncertainty effects), it is not immediately clear how the iBuyer business closure would impact sale outcomes.

To study the effect of the iBuying business closure on sales outcomes, we replace the outcome variable in Equation 1 with the three sales outcomes discussed above. We report these results in Columns 1, 3, and 5 of Table 7. The estimates suggest that after the iBuying business closure, the premium over the Zestimate increased by 1.7% on average (Column 1), the premium over the list price increased by 0.9% on average (Column 3), and the number of days a property stayed on the market decreased by nearly 12.6% on average (Column 5). These results suggest that the iBuyer business closure is also likely to affect buyers' uncertainty, that buyers' uncertainty dominates sellers' uncertainty effects, and that sellers benefit from increased overall uncertainty.

To confirm that other forces beyond those studied in this paper are at play after the iBuyer business closure, we re-estimate Equation 1, including the deviation from the Zestimate as a control. We report these results in Columns 2, 4, and 6 of Table 7. While the deviation coefficients align with those reported in Table 6, the effect of iBuyer business closure on sales outcome is not affected, confirming that forces other than sellers' uncertainty are driving these results.[15]

It is worth noting that the OLS estimates presented in this section ignore sample selection issues in the data; that is, we only observe the sales price and the days on the market for properties sold before our last data collection period. We partially address this concern in Appendix A.2, where we show that the direction of the findings and general conclusions remain consistent when using a Heckman selection model when the outcomes are the sales price premium over the Zestimate and the list price, and a Cox proportional model with right censoring when the outcome is time on market.

We also caution the reader about the generalizability of the findings presented in this section. While the reduced trust in algorithms we document should generalize to other settings, the downstream implication of home sellers benefiting from increased uncertainty may not. This is because the downstream consequences depend on the market structure, such as bargaining and search between buyers and sellers. Therefore, the loss of trust and increased uncertainty help or hurt buyers and sellers differently in other market conditions.

8 Conclusions

As AI and machine learning algorithms become pervasive across several domains, from policymaking to finance to real estate, researchers are considering and studying the consequence of adopting these algorithms, both from the perspective of firms employing them and consumers relying on their output. In this paper, we study how consumers respond to algorithm failures in the context of Zillow, a popular real estate platform that uses machine learning to predict housing market outcomes. We empirically document the effect of one algorithm failure (forecasting future house values for an iBuyer business) on the use of another algorithm (predictions of current house values, known as Zestimates). We show that the failure of

[15]In Table 9 of Appendix A.2, we show that these results are robust to controlling for time on market when the dependent variables are premiums over the list price and the Zestimate, and for list price when the dependent variable is time on the market.

one algorithm decreases consumer trust in another algorithm, consistent with a phenomenon called algorithmic transference. On Zillow, this translates into home sellers deviating more from, and often above, the Zestimate when listing properties for sale. Surprisingly, we provide evidence suggesting that the iBuyer business closure leads to better outcomes for home sellers, who are able to sell their property for more and in less time.

An important caveat and limitation related to this last finding and our paper more generally is that we are able to study the effect of algorithm failure on home sellers but not home buyers, as we do not observe buyers' consideration set and decisions; since sales price and time on market are jointly determined by buyers and sellers, this means that we can only speculate about why we observe beneficial sales outcomes for home sellers. We hope that future research with adequate data can provide more direct evidence of the conjectures we made in this paper.

Despite this limitation, our paper is the first to test the existence of algorithmic transference in the field and find consistent results with the recent behavioral literature that identified this consumer behavior (Longoni et al. 2022). In doing so, this paper further adds to the nascent literature studying the complex relationship between humans and algorithms and offers important implications for firms who are adopting or ready to adopt AI.

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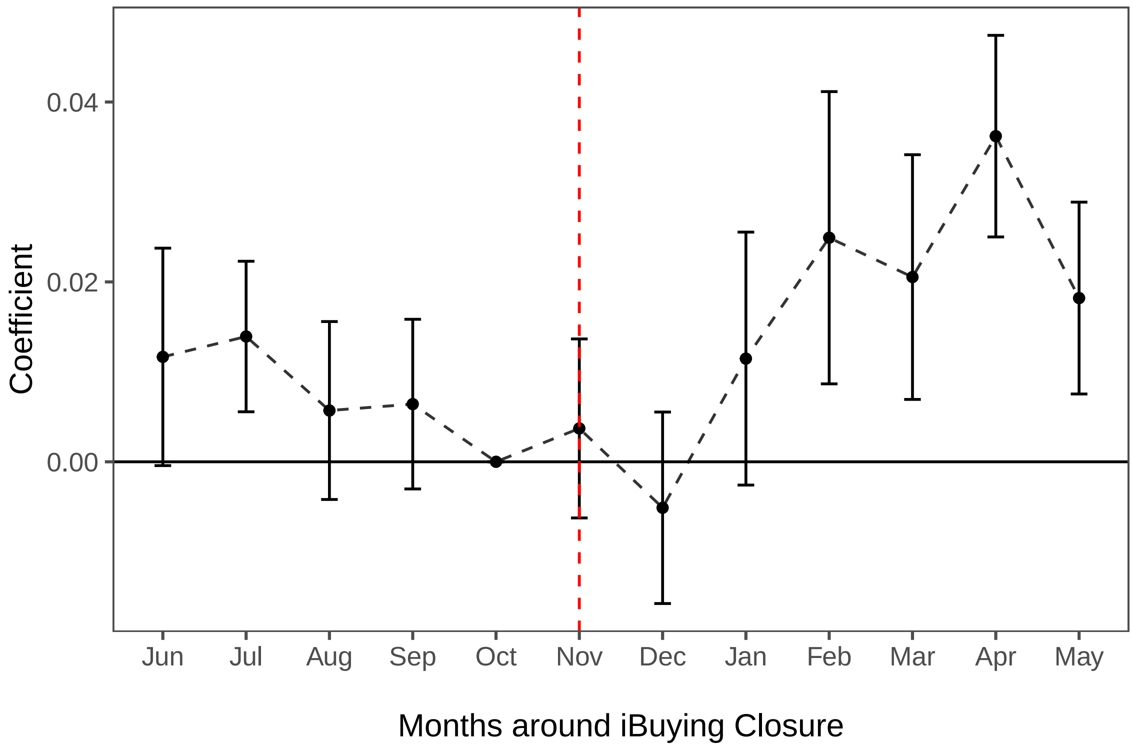

Figure 2: Event study coefficients. Red dashed bar marks iBuyer program closure. Error bars correspond to the 95% confidence intervals.

Table 1: Descriptive statistics

Variable	N	Mean	St. Dev.	Min	25th Perc.	75th Perc.	Max
List and sale outcomes:							
List Price	27,908	496,511	572,119	100,900	199,000	610,000	9,950,000
Sales price	25,021	462,246	470,302	100,100	194,900	590,000	8,500,000
Days on market (List to sold)	24,610	95.097	100.910	1.000	47	98	1,155
Days on market (List to pending)	25,439	46.812	95.199	1	4	48	1,117
Zestimate variables:							
Zestimate	27,908	487,852	548,828	56,600	194,191	613,936	9,950,500
Zestimate range	27,908	18.813	9.319	10.000	12.751	21.478	147.250
List price abs. deviation	27,908	0.043	0.098	0.000	0.003	0.041	1.270
List price deviation	27,908	0.021	0.105	-0.240	-0.012	0.027	1.270
Sales price abs. deviation	25,021	0.068	0.090	0.000	0.019	0.087	1.263
Sales price deviation	25,021	-0.001	0.112	-0.240	-0.053	0.035	1.263
Property characteristics:							
Condo	27,908	0.174	0.379	0	0	0	1
Townhouse	27,908	0.056	0.230	0	0	0	1
Single Family	27,908	0.668	0.471	0	0	1	1
Bedrooms	27,908	3.096	1.284	0	2	4	15
Bathrooms	27,908	2.194	1.016	0	1	3	11
Year Built	27,908	1,939	40.815	0	1,910	1,961	2,022

Note: Sales price and days on market are not observed for properties listed but not sold during our sample period.

Table 2: The effect of the iBuying program closure on the deviation of listing price from the Zestimate

	(1)	(2)	(3)	(4)
After November × Treated Year	0.010***	0.102***	−0.151***	0.014***
	(0.002)	(0.017)	(0.022)	(0.004)
After November	0.020**	0.055	0.046	0.005
	(0.010)	(0.044)	(0.043)	(0.010)
Treated Year	−0.008***	−0.362***	0.221***	−0.023***
	(0.002)	(0.020)	(0.023)	(0.002)
Controls:				
Zipcode FE	Yes	Yes	Yes	Yes
List week FE	Yes	Yes	Yes	Yes
Property characteristics	Yes	Yes	Yes	Yes
Observations	27,908	27,908	27,908	27,908
Adjusted R^2	0.053	0.257	0.250	0.078

Note: OLS estimates with clustered standard errors at the zipcode level. In Column 1, the dependent variable is the absolute listing price deviation from the Zestimate, i.e., abs(Listing price - Zestimate)/Zestimate. In Column 2, the dependent variable indicates whether the listing price set by the seller was above the property's zestimate. In Column 3, the dependent variable indicates whether the listing price set by the seller was below the property's Zestimate. In Column 4, the dependent variable is the percentage deviation between the listing price and property's Zestimate, i.e., y = (Listing price - Zestimate)/Zestimate.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table 3: The effect of the iBuying program closure on absolute listing price deviation from the Zestimate: Robustness checks

	(1)	(2)	(3)
After November × Treated Year	0.010***	0.011***	0.010***
	(0.002)	(0.002)	(0.002)
After November	0.021**	0.019*	0.020**
	(0.010)	(0.010)	(0.010)
Treated Year	−0.009***	−0.009***	−0.005**
	(0.002)	(0.002)	(0.002)
Controls:			
Zipcode FE	Yes	Yes	Yes
List week FE	Yes	Yes	Yes
Property characteristics	Yes	Yes	Yes
Changes in market-level conditions	Yes	Yes	Yes
Changes in Zestimate values	No	Yes	Yes
Listing agent size	No	No	Yes
Observations	27,908	27,908	27,908
Adjusted R^2	0.053	0.072	0.133

Note: OLS estimates with clustered standard errors at the zipcode level. The dependent variable is the absolute listing price deviation from the Zestimate, i.e., abs(Listing price - Zestimate)/Zestimate.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table 4: Changes in housing stock composition

	(1) Bathrooms	(2) Bedrooms	(3) Condo	(4) Townhouse	(5) Single family	(6) Year built
After November × Treated Year	0.037*	0.020	0.011*	−0.0003	−0.001	0.0002
	(0.020)	(0.031)	(0.006)	(0.006)	(0.009)	(0.0004)
After November	−0.094	−0.029	−0.034	0.014	0.016	0.001
	(0.079)	(0.078)	(0.022)	(0.017)	(0.023)	(0.002)
Treated Year	−0.110***	−0.076***	−0.022***	−0.0003	0.001	0.0003
	(0.016)	(0.020)	(0.007)	(0.004)	(0.006)	(0.001)
Controls:						
Zipcode FE	Yes	Yes	Yes	Yes	Yes	Yes
List week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,908	27,908	27,908	27,908	27,908	27,908
Adjusted R^2	0.149	0.183	0.435	0.035	0.500	0.027

Note: OLS estimates with clustered standard errors at the zipcode level. The dependent variables are reported in the header of each column

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table 5: The effect of the iBuying program closure on the absolute deviation of listing price from the Zestimate: Sensitivity analysis

	Without June 2019 to May 2020 (1)	Without June 2020 to May 2021 (2)	Listings in MA (3)	Listings in PA (4)
After November × Treated Year	0.008**	0.012***	0.007**	0.009**
	(0.003)	(0.003)	(0.003)	(0.003)
After November	0.052***	0.021*	0.022	0.014
	(0.019)	(0.011)	(0.018)	(0.012)
Treated Year	−0.0001	−0.012***	−0.004	−0.003
	(0.003)	(0.003)	(0.003)	(0.003)
Controls:				
Zipcode FE	Yes	Yes	Yes	Yes
List week FE	Yes	Yes	Yes	Yes
Property characteristics	Yes	Yes	Yes	Yes
Changes in market-level conditions	Yes	Yes	Yes	Yes
Changes in Zestimate values	Yes	Yes	Yes	Yes
Listing agent size	Yes	Yes	Yes	Yes
Observations	19,916	17,520	9,150	18,758
Adjusted R^2	0.162	0.128	0.109	0.138

Note: OLS estimates with clustered standard errors at the zipcode level. The dependent variable is the absolute listing price deviation from the Zestimate, i.e., abs(Listing price - Zestimate)/Zestimate.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table 6: The relationship between deviating from the Zestimate and sale outcomes

	(1) Premium over Zestimate	(2) Premium over Listing Price	(3) Log days on market
Deviation from Zestimate	0.767^{***}	-0.157^{***}	1.615^{***}
	(0.021)	(0.015)	(0.155)
Controls:			
Zipcode FE	Yes	Yes	Yes
Sale week FE	Yes	Yes	Yes
Property characteristics	Yes	Yes	Yes
Changes in market-level conditions	Yes	Yes	Yes
Changes in Zestimate values	Yes	Yes	Yes
Listing agent size	Yes	Yes	Yes
Observations	25,021	25,021	24,512
Adjusted R^2	0.443	0.140	0.176

Note: OLS estimates with clustered standard errors at the zipcode level. In Column 1, the dependent variable is the percentage difference between the sales price and the Zestimate at the time of listing, i.e., y = (Sales price - Zestimate)/Zestimate. In Column 2, the dependent variable is the percentage difference between the sales price and listing price, i.e., y = (Sales price - Listing price)/Listing price. In Column 3, the dependent variable indicates the log of the number of days the property stayed on the market.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table 7: The effect of the iBuying program closure on sale outcomes

	Premium over Zestimate		Premium over Listing Price		Log days on market	
	(1)	(2)	(3)	(4)	(5)	(6)
After November × Treated Year	0.017***	0.011***	0.009***	0.010***	−0.126***	−0.139***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.045)	(0.043)
After November	−0.0005	−0.007	−0.005	−0.004	−0.178	−0.188
	(0.014)	(0.008)	(0.007)	(0.008)	(0.143)	(0.143)
Treated Year	−0.009***	0.002	0.005**	0.003	−0.197***	−0.174***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.039)	(0.037)
Dev. from Zestimate		0.764***		−0.159***		1.604***
		(0.021)		(0.015)		(0.145)
Controls:						
Zipcode FE	Yes	Yes	Yes	Yes	Yes	Yes
Sale week FE	Yes	Yes	Yes	Yes	Yes	Yes
Property characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Market-level changes in prices	Yes	Yes	Yes	Yes	Yes	Yes
Changes in Zestimate values	Yes	Yes	Yes	Yes	Yes	Yes
Listing agent size	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,021	25,021	25,021	25,021	24,512	24,512
Adjusted R^2	0.059	0.437	0.104	0.132	0.173	0.182

Note: OLS estimates with clustered standard errors at the zipcode level. In Columns 1 and 3, the dependent variable is the sales price deviation from the property's Zestimate at the time of listing, i.e., (Sales price - Zestimate)/Zestimate. In Columns 2 and 5, the dependent variable is the sales price deviation from the listing price, i.e., (Sales price - List price)/List price. In Columns 3 and 6, the dependent variable is the number of days since the property was listed for sale until it was sold.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

A Appendix

A.1 iBuyer effects: Alternative way of computing the sales range variable

In Section 6, we use a linear interpolation to approximate the Zestimate range value on the day of listing. Consider for example a home whose Zestimate range increased from ±5% (20 days before listing) to ±7% (20 days after listing). Since we (researchers) do not observe a continuous change between these snapshots, we performed a linear interpolation that would approximate the Zestimate range on listing day as ±6%. If, however, the Zestimate range does not change linearly, the Zestimate range observed by the home seller on listing day could be less or more than 6%. An error in the approximated Zestimate range value may have an impact on our estimation for role of algorithmic trust. The home sellers' demand uncertainty (and subsequent list price choice) can be driven by both loss in algorithmic trust and the reported Zestimate range. Using a smaller than actual Zestimate range value can overestimate the role of algorithmic trust in home sellers' increased demand uncertainty. In our example, the Zestimate range on listing day can be anything between ±5% to ±7%.[16] A conservative (aggressive) assumption would be that the Zestimate range shifted up from ±5% to ±7% before (after) the listing. Consequently, the home seller observed the maximum (minimum) possible value of ±7% (±5%) at listing. Under this assumption, our measured effect of algorithmic trust would be an underestimate (overestimate).

To cover all the bases, we test these two alternative approaches to recovering the Zestimate range values. We use either the Zestimate range values observed (i) in the latest available snapshot of each property before it is listed for sale (±5% in the earlier example) or (ii) in the earliest available snapshot of each property after it is listed for sale (±7% in the earlier example). Table 8 shows that our main result does not change significantly when

[16] Assuming Zestimate range evolves monotonically, even if not linearly.

using either an aggressive (Column 1) or a conservative (Column 2) approximation of the Zestimate range values.

Table 8: The effect of the iBuying program closure on the absolute deviation of listing price from the Zestimate

	(1)	(2)
After November × Treated Year	0.010***	0.009***
	(0.002)	(0.002)
After November	0.022**	0.019*
	(0.010)	(0.010)
Treated Year	−0.003	−0.005**
	(0.002)	(0.002)
Controls:		
Zipcode FE	Yes	Yes
List week FE	Yes	Yes
Property characteristics	Yes	Yes
Changes in market-level conditions	Yes	Yes
Changes in Zestimate values	Yes	Yes
Listing agent size	Yes	Yes
Observations	27,908	27,908
Adjusted R^2	0.137	0.126

Note: OLS estimates with clustered standard errors at the zipcode level. The dependent variable is the absolute percentage difference between the listing price and its Zestimate, Y = abs(Listing price - Zestimate)/Zestimate.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

A.2 Downstream consequences: Alternative specifications

Below, we present alternative approaches to address potential concerns with our regression analysis of the downstream consequences of reduced trust in Zillow's Zestimate (see Section 7).

Controlling for time on market and list price Our regression results in Section 7 suggest that sale outcomes generally improved for sellers after the iBuying business closure; that is, sales prices were associated with a higher premium over the Zestimate at the listing time and the list price, and properties stayed fewer days on the market. Nonetheless, one concern with these estimates is that they do not account for other dynamics or prices and days on market, such as the fact that houses listed at higher prices tend to stay longer on the market (Knight 2002) or that the number of days a property has been on the market can become a signal of property quality for buyers and ultimately affect sales prices (Tucker et al. 2013).

To examine the impact of such dynamics on our results, we incorporate additional controls into the regression specifications. In Columns 1 to 4 of Table 9, we include the log number of days the property stayed on the market as an additional control. We note that the coefficient for this new control has the expected sign: properties that stay longer on the market sell at a lower price premium over the Zestimate and the list price. Moreover, our main results regarding the effect of the iBuying closure and deviations from the Zestimate at the listing time remain consistent with those presented in Table 6.

In Columns 5 and 6 of Table 9, we include the log of the listing price as an additional control. We note that the coefficient for this new control has the expected sign: properties that start with a higher list price tend to stay longer on the market. Moreover, our main results regarding the effect of the iBuying closure and deviations from the Zestimate at the listing time remain consistent with those presented in Table 6.

Using a Heckman two-step selection model and a Cox proportional hazard model
Another concern with the results in Section 7 relates to the methodology used for the analysis. First, the regression estimates do not account for the fact that we only observe sales price outcomes for houses that eventually sold during our sample period. To account for such sample selection issues, we estimate a similar specification using a two-step Heckman selection model. The results presented in Columns 1 to 4 of Table 10, are generally consistent with those in Table 6, with the exception that the main effect of the iBuying business closure on sales price premium over the Zestimate at the listing time is no longer significant.

Table 9: The effect of iBuying program closure on sale outcomes with more controls

	Premium over Zestimate		Premium over Listing Price		Log days on market	
	(1)	(2)	(3)	(4)	(5)	(6)
After November × Treated Year	0.015***	0.007***	0.006**	0.007***	−0.128***	−0.139***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.043)	(0.042)
After November	−0.003	−0.009	−0.007	−0.006	−0.222	−0.226
	(0.014)	(0.007)	(0.007)	(0.007)	(0.140)	(0.141)
Treated Year	−0.001	0.001	−0.0003	−0.241***	−0.216***	
	(0.003)	(0.002)	(0.002)	(0.002)	(0.038)	(0.037)
Log(Days on market)	−0.020***	−0.026***	−0.026***	−0.025***		
	(0.001)	(0.001)	(0.001)	(0.001)		
Log(List price)					0.589***	0.529***
					(0.055)	(0.053)
Dev. from Zestimate		0.841***		−0.099***		1.394***
		(0.013)		(0.010)		(0.142)
Controls:						
Zipcode FE	Yes	Yes	Yes	Yes	Yes	Yes
Sale week FE	Yes	Yes	Yes	Yes	Yes	Yes
Property characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Market-level changes in prices	Yes	Yes	Yes	Yes	Yes	Yes
Changes in Zestimate values	Yes	Yes	Yes	Yes	Yes	Yes
Listing agent size	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,512	24,512	24,512	24,512	24,512	24,512
Adjusted R^2	0.119	0.570	0.285	0.296	0.184	0.191

Note: OLS estimates with clustered standard errors at the zipcode level. In Columns 1 and 3, the dependent variable is the sales price deviation from the property's Zestimate at the time of listing, y = (Sales price - Zestimate)/Zestimate. In Columns 2 and 5, the dependent variable is the sales price deviation from the listing price, y = (Sales price - List price)/List price. In Columns 3 and 6, the dependent variable is the number of days since the property was listed for sale until it was sold.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Second, the number of days a property stays on the market is a survival event. To better account for the nature of this outcome variable, we estimate a similar specification using a Cox proportional hazard model with right censoring. The results presented in Columns 5 and 6 of Table 10 suggest that the hazard is higher after the iBuying closure (i.e., shorter survival time), which is consistent with the findings from Table 6.

Table 10: The effect of iBuying program closure on sale outcomes; Alternative models

	Premium over Zestimate		Premium over Listing Price		Log days on market	
	(1)	(2)	(3)	(4)	(5)	(6)
After November × Treated Year	0.008*	0.006*	0.009***	0.006*	0.102***	0.108***
	(0.005)	(0.004)	(0.004)	(0.003)	(0.030)	(0.030)
After November	0.0002	−0.0001	−0.001	−0.001	0.200**	0.214**
	(0.002)	(0.001)	(0.001)	(0.001)	(0.091)	(0.091)
Treated Year	−0.015***	−0.002	0.001	−0.002	0.131***	0.117***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.024)	(0.024)
Log(Days on market)	−0.016***	−0.021***	−0.022***	−0.021***		
	(0.001)	(0.0004)	(0.0004)	(0.0004)		
Log(List price)					−0.364***	−0.328***
					(0.022)	(0.022)
Dev. from Zestimate		0.787***		−0.134***		−1.363***
		(0.007)		(0.006)		(0.081)
Controls:						
Zipcode FE	Yes	Yes	Yes	Yes	Yes	Yes
Sale week FE	Yes	Yes	Yes	Yes	Yes	Yes
Property characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Market-level changes in prices	Yes	Yes	Yes	Yes	Yes	Yes
Changes in Zestimate values	Yes	Yes	Yes	Yes	Yes	Yes
Listing agent size	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,908	27,908	27,908	27,908	27,399	27,399
Adjusted R^2	0.061	0.477	0.141	0.161	0.171	0.176

Note: Columns 1 to 4 show estimates for the outcome equation in the Heckman two-step selection model, and Columns 5 to 6 show estimates for a Cox proportional hazard model. In Columns 1 and 2, the dependent variable is the sales price deviation from the property's Zestimate at the time of listing, y = (Sales price - Zestimate)/Zestimate. In Columns 3 and 4, the dependent variable is the sales price deviation from the listing price, y = (Sales price - List price)/List price. In Columns 5 and 6, the dependent variable is the number of days since the property was listed for sale until it was sold.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.